DOCTOR OF PHILOSOPHY

Credit rating divergence and the role of opacity in emerging market banks

Martin Merizalde, Andrea

Award date:
2020

Awarding institution:
Bangor University

Link to publication

Credit rating divergence and the role of opacity in emerging market banks

By Andrea Martin Merizalde

PhD thesis

PRIFYSGOL BANGOR UNIVERSITY

Bangor Business School

April 2020

Declaration and consent

I hereby declare that this thesis is the results of my own investigations, except where otherwise stated. All other sources are acknowledged by bibliographic references. This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree unless, as agreed by the University, for approved dual awards.

Yr wyf drwy hyn yn datgan mai canlyniad fy ymchwil fy hun yw'r thesis hwn, ac eithrio lle nodir yn wahanol. Caiff ffynonellau eraill eu cydnabod gan droednodiadau yn rhoi cyfeiriadau eglur. Nid yw sylwedd y gwaith hwn wedi cael ei dderbyn o'r blaen ar gyfer unrhyw radd, ac nid yw'n cael ei gyflwyno ar yr un pryd mewn ymgeisiaeth am unrhyw radd oni bai ei fod, fel y cytunwyd gan y Brifysgol, am gymwysterau deuol cymeradwy.

Abstract

Prior credit rating literature focused on emerging economies is very limited and often country-specific, despite the significant expansion of the credit rating industry in these countries in recent years. Bank rating studies are particularly scarce, notwithstanding the pivotal role of banks as major funding providers in emerging economies. This thesis addresses these voids in the literature and investigates bank rating divergences between S&P, Moody's and Fitch, the global rating agencies (GRAs), using a cross-country setting (11 emerging economies). Three perspectives are central to the thesis: (i) examining the drivers of national scale ratings (NSR) and global scale ratings (GSR) assignments by S&P; (ii) evaluating the effect of bank opacity on split bank ratings; and (iii) analysing to what extent split bank ratings are driven by systematic components including opacity at the sovereign government level and the sovereign rating ceiling.

The first empirical chapter finds that bank size and competition between GRAs have the strongest effect on the probability of S&P rating assignments. GSR (NSR) assignments by S&P are more likely for larger (smaller) banks, although there exists a dependency on whether the bank has prior NSR (GSR) ratings. Fitch ratings potentially substitute S&P ratings, while Moody's ratings complement S&P. The second empirical chapter uses bank size, capital, liquidity and profitability as proxies of bank opacity. The analysis demonstrates that bank opacity increases the probability of split bank ratings. Also, split-rated banks are more likely to experience future rating migrations than non-split rated banks, and wider rating differences have the strongest impact. The third empirical chapter presents evidence of a significant effect of split sovereign ratings and the ceiling effect on split bank ratings. The probability that S&P assigns bank ratings in a more conservative manner than Moody's (Fitch), increases when S&P assigns lower sovereign ratings than Moody's (Fitch). The same result is achieved when Moody's assigns lower sovereign ratings than Fitch. Moreover, bank rating disagreements are more sensitive to split sovereign ratings when the ceiling effect of the GRA that assigns higher bank and sovereign ratings prevails.

The thesis provides highly original contributions to the literature. New evidence on the rating dynamics between NSR and GSR assignments in emerging economies offers a novel perspective on the study of bank rating determinants. The thesis also provides clear insights on the strong effect of asset opacity and information quality on split bank ratings in emerging economies. These issues are of interest for policymakers, banks and other market participants due to their potential impact on debt issuance costs and foreign investment flows.

Acknowledgements

First of all, I would like to thank my supervisors, Professor Owain ap Gwilym and Dr Rasha Alsakka, for all their guidance, support and advice during my PhD. I feel extremely fortunate to have supervisors who have also been my mentors, sharing their valuable expertise and providing insightful discussions about my research. Their encouragement, patience and confidence in my work have been invaluable throughout the PhD. I am also grateful with Bangor Business School for the PhD scholarship received to pursue my Doctoral studies and to Professor Aziz Jaafar for his constructive comments and suggestions.

I would also like to thank all my PhD colleagues for the stimulating discussions during the PRSS and for making my PhD a pleasant journey. Also, a big thanks to the staff at Bangor Business School, especially Rachel Parry for her invaluable help coordinating my tutorials. My sincere gratitude also to my friends for their support and advice during my studies, specially to Marybeth, Calvin, Laurence, Lana and Quang for the interesting discussions and being unconditional friends, which has been essential during these academic years.

I also want to express my gratitude to my family in Colombia for believing in me and have accompanied me during my academic endeavours. And finally, special thanks to Sebastian, my partner, who inspired me to pursue my doctoral degree and who has been by my side throughout this PhD journey, discussing my findings and giving me his patience, encouragement and unconditional support.

Contents

List of tables

List of supporting tables

List of figures

Abbreviations and acronyms

ABS	Asset-backed securities
BBVA	Banco Bilbao Vizcaya Argentaria
CBR	China Bond Rating
CBRS	Canadian Bond Rating Service
CCI	Control of corruption Index
CDO	Collateralized debt obligations
CESR	Committee of European Securities Regulators
CI	Corruption index
CRAs	Credit Rating Agencies
DBRS	Dominon Bond Rating Service
DCR	Duff & Phelps Credit Rating Agency
EBA	European Banking Authority
ECAI	External Credit Assessment Institutions
EJ	Egan Jones Ratings Co
EPS	Earnings Per Share
Eq(s).	Equation(s)
ESMA	European Securities Markets Authority
EU	European Union
FINMA	Swiss Financial Market Supervisory Authority
FOIA	Freedom of Information Act
FSB	Financial Stability Board
GDP	Gross Domestic Product
GRAs	Global Rating Agencies
GSR	Global Scale Rating
ID-CREM	Interactive Data Credit Ratings in Emerging Markets
IMF	International Monetary Fund
IOSCO	International Organization of Securities Commissions
IRAs	International Rating Agencies
JCR	Japan Credit Rating Agency
KBRA	Kroll Bond Rating Agency
KIS	Korea Investors Service, Inc.
KR	Korea Ratings
LT	Long-Term

MBS	Mortgage-backed securities
ME	Marginal effects
MEM	Marginal effects at the means
NHIC	Non-High-Income Countries
NICE	National Information & Credit Evaluation
NRAs	National Rating Agencies
NRSRO	Nationally Recognized Statistical Rating Organization
NSR	National Scale Rating
N/A	Not applicable
Obs	Observations
OCR	Office of Credit Ratings
OECD	Organisation for Economic Co-operation and Development
OI	Asset Opacity Index
Q	Quarter
ROA	Return on Assets
ROAA	Return on Average Assets
R&I	Japan Rating & Investment Information
S&P	Standard & Poor's
SEC	U.S. Securities and Exchange Commission
SME	Small and Medium Size Enterprises
Std. Dev.	Standard deviation
WGI	Worldwide Governance Indicators

Country codes[1]

AR	Argentina
BR	Brazil
CN	China
CO	Colombia
ID	Indonesia
KZ	Kazakhstan
MX	Mexico
NG	Nigeria
RU	Russian Federation (The)
TH	Thailand
ZA	South Africa

[1] The country codes correspond to the ISO codes (Alpha-2) according to the ISO 3166 international standard (IBAN, 2019).

Chapter 1 Introduction

1.1 Introduction

With increased globalization and integration, emerging economies are receiving more foreign portfolio investment (FPI) and foreign direct investment (FDI). Although FPI flows to emerging economies are more volatile after the taper tantrum[2] of 2013 (UNCTAD, 2017), they have supported the growth of the bond markets. One example of the increase in the FPI is the bond market in China, which has grown from US$1 trillion in 2000 to US$5.5 trillion in 2016 (Hu et al., 2019). With a greater volume of bonds issued worldwide and some regulations mandating the use of credit ratings (Marandola, 2016), the credit rating industry in emerging economies has experienced a meaningful expansion (Jiang and Packer, 2017, 2019; Yang et al., 2017; Livingston et al., 2018). Nevertheless, the specific country characteristics, such as a developing financial system, weaker institutional environment, high information asymmetries, and political instabilities have influenced how the credit rating industry has been shaped and grown in emerging economies.

An expanding presence of national credit rating agencies (NRAs), which are credit rating agencies (CRAs) that assign domestic ratings, characterises the credit rating industry in emerging economies. Marandola (2016) documents the presence of more than 200 NRAs operating worldwide, mainly established in Asia and Latin America.[3] She argues that the strong presence of NRAs in these regions is associated with two key factors. Firstly, a response to regulations, as credit ratings are compulsory for issuers and instruments in the capital markets. Secondly, the efforts of governments and bilateral institutions (such as the International Financial Corporation, IFC) to improve the access to funding for small and medium sized companies in the domestic capital markets. There is a positive impact in the development of the financial system associated with the presence of NRAs (Ferri and Lacitignola, 2010; Marandola, 2015). Along with stronger banking regulation and a suitable demand for credit ratings related to NRAs' presence, this has created the conditions for the expansion of S&P, Moody's and Fitch, the three global rating agencies (GRAs), in emerging economies. This expansion has been mainly achieved through affiliates and joint ventures (indirect presence), as several emerging countries have regulatory constraints that have prevented or discouraged GRAs from entering directly (e.g. South Korea), although the situation is dynamic e.g. in China.

[2] The prospects of the relaxation of the bond-buying program and tightening of the monetary policy of the U.S. Federal Reserve, known as 'taper tantrum' starting in May 2013 has pervasive effects in several emerging economies, causing an increase in bond yields, fall in equity prices and exchange rates depreciation (Sahay et al., 2014).

[3] See Table 3.1 for the list of emerging and developing countries classified as Latin America and the Caribbean.

The particular composition of the credit rating industry in emerging markets, its expansion and impact on the financial system and capital markets, has sprouted an academic interest in NRAs in recent years, although published research in this area continues to be scarce. The most likely reason for the scarcity of research on NRAs is the availability of GRAs' information and the possibility of conducting cross-country comparisons using global ratings. Moreover, GRAs' registration with rating supervisors in the US (U.S. Securities and Exchange Commission - SEC) and in Europe (European Securities Markets Authority - ESMA), entails access to better reporting standards, facilitating the data collection and analysis when examining the credit rating industry in the US and the EU. Thus, research on NRAs or GRAs' national scale ratings in emerging economies is usually country-specific, because unlike the global scale ratings, sovereign risk is not incorporated in ratings assigned on a national rating scale. Hence, national ratings are only suitable for comparing rated companies in the same country. Recent investigations on national ratings are focused on China (e.g. Jiang and Packer, 2017; Livingston et al., 2018; Hu et al., 2019), and Korea (e.g. Ferri et al., 2013; Joe and Oh, 2017; Yang et al., 2017), where the credit rating business has flourished with the expansion of the bond markets.

These studies on national and global ratings from emerging economies highlight the strong market impact that GRAs have through their alliances (joint ventures and affiliations) with domestic NRAs, while suggesting that ratings from NRAs continue to have reputational value. Of greater relevance for this thesis, the investigations (cited above) highlight the meaningful role of national scale ratings from GRAs in emerging economies and the transfer of the reputational value of GRAs' global ratings to the national scale ratings through their affiliates and partnerships. However, research on GRAs' national and global scale ratings is absent from the literature, although companies can have both ratings assigned by GRAs instead of having national ratings from NRAs and global ratings from GRAs. Therefore, the segmentation in the credit rating industry between NRAs and GRAs raised by Ferri and Lacitignola (2010) for the Asian market, could not remain effective, if the expansion of GRAs' business through the indirect presence and the national scale ratings offered by these affiliates to GRAs are considered. Moreover, since assigning a national or a global rating from a GRA should be related to the type of risk being evaluated, and the characteristics of the rated companies can change (i.e. expansions, M&A, overseas issuance, etc.), having ratings from a GRA should reflect a complementary and dynamic process between national and global ratings, instead of a static choice between those two types of ratings.

Besides the growth in bond and equity markets and the presence of NRAs, the expansion of the GRAs in emerging economies has also been a result of tighter banking regulation, which has stimulated the use of GRAs' credit ratings as an instrument of policy (Marandola, 2016). Since the access of borrowers to the capital markets is constrained by high information asymmetries, bank loans still constitute the main source of funding in emerging economies (Nagano, 2018). As a result, GRAs have an active role in the financial system development through bank ratings. The downside of the high dependence on the banking industry in emerging economies is that bank loans are less exposed to public scrutiny, and the weak institutional environment in emerging economies impedes public monitoring of the borrowers (Goodell and Goyal, 2018). Moreover, the typically low level of government transparency in emerging economies also encourages risk-taking behaviour in banks (Chen et al., 2015). Therefore, in such countries, banks also induce greater opacity for other economic sectors and the government. Prior research shows that higher asset opacity increases rating disagreements (Morgan, 2002; Iannotta, 2006; Livingston et al., 2007), and that banks have higher levels of asset opacity compared to other industries (e.g. Morgan, 2002; Blau et al., 2017; Fosu et al., 2017, 2018).

Besides the inherent opacity of the banking sector, the prior literature postulates that GRAs' uncertainty when rating banks should be higher due to the effect of a lack of transparency at sovereigns and borrower levels. Thus, split ratings (rating disagreements) between GRAs in emerging economies are likely to be more frequent and persistent than in developed economies. However, split bank ratings in emerging economies is an issue that has not been discussed in the literature, as investigations on split bank ratings incorporate only data from developed economies (Morgan, 2002; Iannotta, 2006). Moreover, opacity also has an impact on future rating changes, as harsher split ratings (in notches) have a stronger effect on the subsequent rating migrations (Livingston et al., 2008; Alsakka and ap Gwilym, 2010c). However, the link between split bank ratings and future rating changes in emerging economies has not been examined by prior literature. This remains true despite its relevance from an investor perspective, i.e. in a context of high information asymmetry, it represents an additional tool to anticipate the further deterioration of debt issuers' credit quality.

Research on sovereign split ratings in emerging economies reveals that sovereign opacity, measured through the political risk and information quality, is an important factor that helps to explain those disagreements (Vu et al., 2017). Hence, sovereign opacity should also increase the uncertainty in the banking industry in emerging economies, as sovereign risk can be transmitted to the industry[4] through the sovereign ratings (Williams et al., 2013, 2015; Alsakka et al., 2014; Huang and Shen, 2015; Adelino and Ferreira, 2016; Drago and Gallo, 2017). Furthermore, the

[4] BIS (2011) identifies four channels of transmission of the sovereign risk to bank risk: bank portfolio holdings of public debt, a collateral channel, a rating channel and a guarantee channel (see Section 6.2.3).

literature shows that GRAs' sovereign ratings potentially have a "home bias" (Luitel et al., 2016; Tennant et al., 2018; Yalta and Yalta, 2018; Park et al., 2019) and a subjective component (qualitative features) (De Moor et al., 2018). These features are more detrimental in emerging economies; therefore, it could be argued that split sovereign ratings have also a significant impact on split bank ratings in emerging economies. Moreover, bank ratings continue bounded by the sovereign ceiling[5] in emerging economies, although GRAs' no longer apply an absolute and strict ceiling rule when rating non-sovereigns (Williams et al., 2013, 2015; Huang and Shen, 2015), which should also be a factor influencing bank ratings.

Considering the voids in the credit rating literature which are identified above, this thesis aims to contribute to knowledge by providing new evidence on credit rating divergence and the role of opacity in emerging market banks. This objective is addressed from three perspectives. Firstly, by examining the drivers of national and global scale ratings assigned by S&P in banks from emerging economies, while including the ratings of the other two GRAs as the effects of competition (Chapter 4). The second perspective focuses on the determinants of split bank ratings assigned by GRAs in emerging economies and the impact of those disagreements on future rating changes (Chapter 5). Lastly, by analysing the impact of the systematic component of split bank ratings through split sovereign ratings, the thesis incorporates the influence of sovereign opacity in bank ratings upon bank rating disagreements (Chapter 6).

Chapter 4 examines the drivers of S&P national scale ratings (NSR) and global scale ratings (GSR) assignments using a panel dataset of 4,284 observations.[6] This includes a sample of 145 banks from 11 emerging economies[7] which have long-term issuer national and/or global scale ratings assigned by S&P, for the period from 2006 to 2015. As the objective is to examine the propensity of S&P assigning an NSR or a GSR, Chapter 4 incorporates a binary probit approach, which is commonly used in credit rating literature (Morgan, 2002; Bowe and Larik, 2014). Chapter 5 investigates the drivers of split bank ratings between GRAs and the impact of those split ratings upon future bank rating changes. It employs a panel dataset of 862 observations (78 banks) with global ratings assigned by S&P and Moody's; 798 observations (76 banks) with global ratings assigned by S&P and Fitch; and 813 observations (64 banks) with global ratings assigned by

[5] The sovereign ceiling or ceiling effect occurs when the sovereign rating is the maximum rating assigned to non-sovereign issuers within a country (Williams et al., 2013).
[6] This refers to the total sample, including 145 rated banks with long-term issuer national and/or global scale ratings and 275 banks not rated by S&P. See further details of the sub-samples in Table 4.2.
[7] The sampled countries are selected based on financial data availability in the Bankscope database, along with relevant rating data availability. The countries are Argentina, Brazil, China, Colombia, Indonesia, Kazakhstan, Mexico, Nigeria, Russia, South Africa, and Thailand.

Moody's and Fitch (813) from 10 emerging countries,[8] for the period from 2008 to 2015. Furthermore, the thesis also includes ordered probit specifications as a robustness test, which is another approach frequently used in the literature on split ratings (Iannotta, 2006; Livingston et al., 2007), to consider the notch-differences between ratings assigned by each pair of GRAs. Chapter 6 examines the impact of split sovereign ratings and the ceiling effect on bank rating disagreements, using a panel dataset of 1,898 observations (92 banks) with global ratings assigned by S&P and Moody's; 1,767 observations (90 banks) with global ratings assigned by S&P and Fitch; and 2,423 observations (113 banks) with global ratings assigned by Moody's and Fitch from 10 emerging economies[9], for the period from 2008 to 2015.

The key findings of the empirical chapters are as follows. Chapter 4 demonstrates that financial ratios, the sovereign rating level and the effects of competition between GRAs are the main drivers of S&P bank rating assignments. NSR are relevant for the domestic market and NSR assigned by S&P can influence GSR assignments in the future. NSR become more informative than GSR when the sovereign rating is high (low sovereign risk), while GSR are relevant in countries with high sovereign risk. Lastly, the effects of competition are not symmetric. Moody's and S&P seem to complement[10] each other's rating assignments. In contrast, Fitch rating assignments compete with S&P in the domestic market. Overall, the results highlight that NSR have a strong relation with GSR, playing a crucial role in the banking sector of emerging economies. This finding is unique and there is no comparable cross-country evidence in the prior literature.

Chapter 5 tests *the opacity hypothesis* in GRAs' split ratings for banks in emerging economies. The *opacity hypothesis* was initially introduced by Morgan (2002) for US banks. It asserts that GRAs' split bond ratings are not a result of random errors in the rating process but are related to GRAs' response to firms' asset opacity. The hypothesis has also been confirmed for split ratings of European banks (Iannotta, 2006) and for US corporate split ratings (Livingston et al., 2007; Bowe and Larik, 2014). The results of Chapter 5 suggest that split bank ratings (in emerging markets) are not a consequence of random rating errors. Instead, they reflect differences in GRAs' credit opinions on banks' asset opacity, confirming the *opacity hypothesis*. Moreover, the split ratings in the studied sample tend to be lopsided, with one GRA consistently assigning lower ratings (Morgan, 2002; Livingston et al., 2007, 2010). The descriptive analysis in Chapter 5 shows

[8] For the GRA pairs: S&P and Moody's, and Moody's and Fitch, the sample comprises banks from 9 countries, excluding Argentinean and Nigerian banks, and for S&P and Fitch, the sample includes bank ratings from 10 countries, excluding Argentinean banks (see further details in Section 5.4.3).

[9] Argentinean and Nigerian banks are excluded from the sample rated by S&P and Moody's (see further details in Section 6.4.1).

[10] Moody's rating assignments increase the probability of S&P rating assignments, while the presence of a Fitch rating reduces the likelihood of S&P rating assignments.

that S&P tends to be more conservative when assigning bank ratings compared to the other two GRAs, as in the sample, 80% of the split ratings observations have lower S&P ratings. The results differ from the conservative behaviour by Moody's reported in Morgan (2002) and Iannotta (2006). The second part of Chapter 5 shows that split bank ratings have a strong influence on future rating migrations, especially future bank rating upgrades (consistent with Livingston et al., 2008; Alsakka and ap Gwilym, 2009, 2010c). Furthermore, the wider the split bank rating differentials (in notches), the stronger is the effect on future bank rating changes.

The results of Chapter 6 reveal that besides the opacity of bank assets (see Chapter 5), opacity at the sovereign government level is another key driver of split bank ratings. Furthermore, the sovereign ceiling has a significant influence on bank rating disagreements, implying that both split sovereign ratings and the sovereign ceiling can capture the systematic component of split bank ratings, and this is particularly applicable in emerging economies. When a GRA assigns an inferior (superior) sovereign rating, the likelihood of assigning an inferior (superior) bank rating is higher. Moreover, the effect of split sovereign ratings on split bank ratings is significantly influenced by the sovereign ceiling, although the ceiling effect differs between each pair of GRAs. The estimations also show that split sovereign ratings are not symmetric, with S&P tending to be more conservative (rating lower) than Moody's and Fitch, corroborating the results for split sovereign ratings in emerging economies found by Vu et al. (2017).

This thesis contributes to the existing literature in several ways. Firstly, emerging economies are an interesting framework, as their high information asymmetries and the weak institutional environment amplifies opacity in banks' balance sheets. The literature only contains scarce examples of investigations on split bank ratings, which are limited to the US (Morgan, 2002) and Europe (Iannotta, 2006). This thesis takes an original direction by analysing bank opacity alongside the effects of sovereign opacity as drivers of split bank ratings. Secondly, the thesis investigates the relationship between NSR and GSR, for which there is no prior evidence in the literature. Lastly, by including all three pairs of GRAs, the thesis adds a new dimension to the findings of split bank rating literature, which analyses split bank ratings using only two GRAs.

The remainder of the thesis is organised as follows. Chapter 2 discusses the most pertinent institutional features of the credit rating industry. Chapter 3 reviews the most relevant literature on credit ratings and the role of CRAs in emerging economies. Chapter 4 examines the drivers of banks' S&P rating assignments on both national and global rating scales in emerging economies. Chapter 5 investigates the determinants of split bank ratings in emerging economies and their impact on rating migrations. Chapter 6 takes a unique approach to identify a systematic component in split bank ratings. Chapter 7 presents the conclusions and suggestions for future research.

Chapter 2 Background of the credit rating industry

2.1 Introduction

The purpose of this Chapter is to outline the conceptual structure of the credit rating industry. By describing the legal framework within which credit rating agencies (CRAs) operate, the type of CRAs and ratings they offer and their business model, this Chapter complements the literature review developed in Chapter 3 and presents the setting for the investigations in the empirical chapters.

The literature on credit ratings is focused on the operation of the largest CRAs: S&P, Moody's and Fitch, namely the global rating agencies (GRAs). However, this Chapter shows that there are more than 200 CRAs operating worldwide specialised in different types of ratings. Domestic CRAs assign only national ratings; regional CRAs assign regional and national ratings and international CRAs like the three GRAs, can assign national and global scale ratings. This Chapter is focused on describing two of the different types of available ratings: global scale ratings and national scale ratings. Both global and national scale ratings offer long-term and short-term ratings to issuers, and global ratings usually are offered in foreign and local currency. The Chapter also gives an overview of the active supervisors of the credit rating industry, which regulate the rating practices of the CRAs. The Chapter concludes with the description of the compensation models currently used for the solicited ratings: the issuer-pay and the subscriber-pay model. Each has advantages and drawbacks that have been studied by the credit rating literature.

The Chapter is organised as follows: Section 2.2 presents the objectives, type, and characteristics of CRAs and the regulation on the rating practices, introducing the concepts of national and international CRAs. Section 2.3 presents the issuer credit rating scales, which are later used in the empirical chapters. Section 2.4 provides a review of the business model of the CRAs and the academic debate around the different models, and Section 2.5 concludes.

2.2 Composition of the credit rating industry

CRAs provide an independent public opinion about the financial quality of a borrower (e.g. issuer: government, corporate, financial institution, etc., or an issue: bonds or another financial liability). By evaluating the capacity of the borrowers to meet their obligations on time and according to the terms established with the creditors (e.g. bondholders), the CRAs assess their probability of default. Because of the risk assessment involved in the ratings, CRAs are considered institutions capable of reducing information asymmetries between market agents (Duff and Einig, 2009; White, 2010; Camanho et al., 2012).

The operation of the CRAs can be limited to national ratings or have international coverage. CRAs operating at the national level are supervised by local authorities, which explains the substantial differences in the degree of regulatory requirements across countries (FPRI, 2013). There are also two supervision authorities with a wider scope of supervision, including domestic CRAs and CRAs with international operations: the Office of Credit Ratings (OCR) from the U.S. Securities and Exchange Commission (SEC) and the European Securities and Markets Authority (ESMA). The Office of Credit Ratings (OCR) is created by the 2010 Dodd-Frank Act[11] in the United States, as part of the SEC. OCR aims to strengthen the regulation and promote the transparency in the credit rating industry, by supervising the practices and law compliance of the CRAs registered with the SEC as Nationally Recognized Statistical Rating Organization (NRSRO). According to the SEC (2018), there are ten CRAs registered as NRSRO. As Table 2.1 shows, most NRSROSs have international coverage, offer solicited and unsolicited ratings and have a diversified portfolio of ratings.

ESMA is created by the European Commission in July 2011, as a replacement for the Committee of European Securities Regulators (CESR). Among its activities, ESMA is the direct supervisor of CRAs within the European Union (EU) and also of non-EU CRAs which require a certification of their rating.[12] The purpose of ESMA is to enforce the regulation of the credit rating industry, aiming at improving the quality of the ratings. There are 36 CRAs registered with ESMA, and from those CRAs, three: S&P, Moody's and Fitch have subsidiaries in Europe also registered with

[11] Dodd-Frank Wall Street Reform and Consumer Protection Act is a reform made by the Obama government to promote US financial stability. The Title IX, Subtitle C of the Dodd-Frank Act is focused on the regulation of CRA.

[12] According to ESMA regulation 1060/2009, CRAs established in third countries may apply for certification. Once they get certified, the credit ratings of entities established, or financial instruments issued in third countries may be used in the EU for regulatory purposes without being endorsed.

ESMA. Thus, the total of CRAs registered with ESMA is 51.[13] From the 36 CRAs certified with ESMA, four are from Japan, Mexico and the USA (see Table 2.2 for the list of CRAs registered or certified with ESMA as of March 2019).[14] The majority offers solicited ratings paid by the issuers and unsolicited ratings (the type of remuneration model is discussed in detail in Section 2.4). Although regulatory reforms of CRAs in the EU aims, among other objectives, to reduce the over-reliance of market participants on a few CRAs, there is mixed evidence on the effect of the overreaction of the market to rating actions by the largest CRAs (S&P, Moody's and Fitch) after the establishment of ESMA, indicating that the new regulation is still in consolidation (Alsakka et al., 2015). Additionally, CRAs that are registered or certified by ESMA are also recognized as an External Credit Assessment Institutions (ECAI) by the European Banking Authority (EBA). The recognition as an ECAI is aligned with the enhancement of the credit quality according to Basel II principles. There is one CRA registered as ECAI which is not registered with ESMA: Rating and Investment Information, Inc. (R&I), a Japanese CRA approved as an ECAI in Japan, Hong Kong and Malaysia,[15] which has a diversified rating business.

There are other regulatory entities, not classified as rating supervisors, which grant recognition to CRAs. Supervised entities use the recognised CRAs to calculate their capital requirements. For instance, the Swiss Financial Market Supervisory Authority (FINMA) in Switzerland acts as a certification authority for CRAs with business in Switzerland. FINMA recognizes CRAs' quality standards through specific requirements based on the standards established by the International Organization Of Securities Commissions (IOSCO) and the Basel Committee on Banking Supervision (FINMA, 2012). The CRAs recognised by FINMA are six: S&P, Moody's, Fitch Ratings, Dominion Bond Rating Service (DBRS), Fedafin AG and Scope Ratings (FINMA, 2018). There are other regulatory bodies worldwide like the Japan Financial Services Agency (FSA, 2014) in Japan, the China Securities Regulatory Commission (CSRC, 2007) in China and the Canadian Securities Administrators (CSA, 2012) in Canada.

To tackle the quality of regulation and the dispersion of regulatory practices and procedures regarding CRAs operating overseas, IOSCO created the IOSCO CRA Task Force (which later becomes the IOSCO Committee 6 on Credit Rating Agencies) (IOSCO, 2013). One of the main tasks of IOSCO Committee 6 (C6) has been to enhance the collaboration between regulators and

---

[13] Regulation (EC) No 1060/2009 of the European Parliament and of the Council of 16 September 2009 on CRA amended by Regulation (EU) No 513/2011 of the European Parliament and of the Council of 11 May 2011.

[14] Table 2.2 excludes the subsidiaries of S&P, Moody's and Fitch, which are presented in Table 2.3.

[15] According to R&I web page: https://www.r-i.co.jp/en/docs/policy/regulation02.html, R&I is recognized as an eligible CRA by Bank Indonesia with regard to regulations on foreign currency-denominated external debt of non-bank corporations, and by the Stock Exchange of Thailand concerning the issuance of baht-denominated bonds or debentures by foreign entities or their subsidiaries and affiliates in Thailand.

increase the quality of the supervision and the availability of information on the credit rating industry. Currently, the SEC and ESMA are part of the entities cooperating with C6.

Basel Committee (2000) highlights that around 130 CRAs were operating worldwide in 1999. Subsequently, Langohr and Langohr (2010, p. 23) estimate that 150 CRAs were operating worldwide in 2010. More recently, a dataset build by Marandola (2016) shows that 205 CRAs are operating locally in 131 countries, and more than 100 affiliates or branches of Moody's, S&P and Fitch in 46 countries. Marandola (2016) suggests that local CRAs, also called national rating agencies (hereafter, NRAs), cluster by region, driven by the development of the financial system, the presence of associations of CRAs, or by strong financial interconnections in the countries of the same region. Furthermore, the study highlights that the highest number of NRAs are located in North America, Asia and Latin America.[16] She also finds that the number of NRAs is higher in English speaking countries and in countries with high GDP per capita. Because the focus of Marandola (2016) is building a dataset of NRAs, the investigation has the limitation that it does not present any information regarding the number of ratings assigned by these NRAs. This hampers the possibility of analysing the NRAs' industry concentration and market share.

In contrast with the information available on NRAs, the CRAs registered with the SEC and ESMA have to report the number of ratings assigned. The report allows the estimation of the level of concentration of the CRAs regulated by these supervisors. According to the SEC (2018), three CRAs, called hereafter Global Rating Agencies (GRAs), dominate the rating business: Standard & Poor's (S&P), Moody's Investor Service (Moody's) and Fitch Ratings (Fitch). By the end of 2018, the percentage of outstanding credit ratings is 49.2% by S&P, 33.1% by Moody's and 13.5% by Fitch Ratings, which represents 95.8% of the total outstanding credit ratings from the CRAs registered with the SEC.[17] In their report, the SEC mentions that the ratings of government securities represent 76% of the total outstanding ratings. Moreover, using the inverse of the Herfindahl-Hirschman Index,[18] the SEC indicates that the credit rating industry is highly concentrated. Similarly, ESMA measures the market share of CRAs as the "annual turnover generated from credit rating activities and ancillary services at group level in the EU for that CRA or group of CRAs" (ESMA, 2018; pp. 5), and the results are similar to the SEC. S&P has a market share of 46.3%, Moody's of 32% and Fitch of 15.10%.[19] The high market share of the GRAs

[16] See Table 3.1 for the list of emerging and developing countries classified as Latin America and the Caribbean.
[17] The ratings include the categories of: financial institutions, insurance companies, corporate issuers, asset-backed securities and government securities (sovereign and public finance).
[18] According to Rhoades (1993) the Herfindahl-Hirschman Index is a statistical measure of concentration commonly used by the Department of Justice and the Federal Reserve to analyse mergers.
[19] According to ESMA, the type of ratings analysed are: corporate (non-financial, financial, and insurance ratings), sovereign ratings, structured finance ratings and covered bond ratings.

reported by SEC and ESMA has raised concerns about the oligopolistic characteristics of the credit rating industry (Bolton et al., 2012; Saka, 2018), and the SEC and ESMA supervision of CRAs has been under scrutiny for increasing the certification role of the CRAs registered with them (White, 2010; Deb et al., 2011).

GRAs have worldwide presence directly or indirectly through affiliates, and a broad portfolio of ratings (sovereign, corporate, financial sector, insurance, funds, structured finance, and derivates, among other ratings). Their extensive portfolio of international ratings allows them to have a wider view of the dynamics between the government and the economic sectors. In comparison, international rating agencies (hereafter, IRAs) have less diversification of their services and several are specialized in specific segments and/or regions.[20] The biggest IRAs, measured by the number of outstanding credit ratings reported by the SEC (2018), are DBRS (2.3%) and Egan-Jones Ratings Co. (EJ) (0.8%).[21] ESMA (2018) shows that the IRAs with the highest market share among the CRAs registered or certified are: DBRS (1.88%), The Economist Intelligence Unit (0.86%) and Cerved Rating Agency (0.82%).[22]

Marandola (2016) notes that GRAs usually start operations in countries where the financial system has a certain level of development and where there is strong supervisory authority for the banking industry. She also indicates that the presence of GRAs usually follows the presence of NRAs, as the latter are a proxy of the level of demands for credit ratings. GRAs offer their rating services by direct operation through offices or subsidiaries in a country or indirectly through affiliates. Based on the report by S&P Global Ratings (2018) to the SEC, S&P has 115 subsidiaries, from which 27 are in the rating business (See Table 2.4).[23] Moody's (2018b) has 102 subsidiaries: 34 are in the rating business (see Table 2.5 Panel A) and has 6 partnerships or alliances[24] (See Table 2.5 Panel B). Fitch Ratings (2019) reports 33 majority-owned subsidiaries, of which 6 are affiliates.

According to the literature on the multinational expansion of foreign companies, the choice between establishing a fully-owned subsidiary or an affiliate and the different levels of equity

[20] As Table 2.2 shows, Scope Ratings AG is focused on Germany, France, United Kingdom, and Netherlands; Euler Hermes Rating GmbH is focused mostly on corporate ratings of EU and Germany; INC Rating rates public entities and its focus is EU.
[21] The total outstanding rating percentage reported by the SEC (2018) includes GRAs.
[22] The total outstanding rating percentage reported by ESMA (2018) includes GRAs.
[23] The business description of S&P subsidiaries is collected from CapitalIQ, the web pages of the subsidiaries and Bloomberg.
[24] The only GRA with a description of the rating agreements with their partners or allies is Moody's. For instance, Moody's indicates in their web page that the agreement with ICRA Ltd. (fully-owned subsidiary) "includes an exchange of global and local market expertise, selective joint research publications, joint credit seminars for the benefit of Indian market participants, and training of ICRA credit analysts". In the case of Midroog, another majority-owned subsidiary, and Meris, a joint venture between Finance & Banking Consultants International and Moody's, Moody's indicates that both IRAs use their own rating methodologies, policies and procedures, and have an independent technical committee (Moody's, 2019a).

ownership are related to the particular characteristics of the country and its industry development (see Pan, 1996). Furthermore, research indicates that the degree of ownership is linked to cultural distance and diversity (Uhlenbruck, 2004; De Jong and van Houten, 2014) and regulatory framework (Yiu and Makino 2002). Furthermore, the language, the level of research and development, the degree of foreign direct investment in the country and the size of the affiliate are also suggested as variables that influence the decision of selecting joint ventures or whole ownership subsidiaries (Demirbag et al. 2010). Literature highlights regulation as the main limitation of the direct operation of GRAs. Ferri et al. (2013) show that in South Korea GRAs face heavy accreditation requirements from regulators for establishing subsidiaries (instead of affiliates), which has limited the direct presence of GRAs. As a consequence, GRAs operate through NRAs affiliated to GRAs. Likewise, China prohibits foreign CRAs to assign domestic bond ratings, to protect their credit rating industry. Thus, in China GRAs operate through partner NRAs (Livingston et al., 2018).

2.3 Credit rating scales

Ratings can be assigned based on the global scale, which incorporates the sovereign risk in the evaluation of the creditworthiness of an issuer (or issue), or based on the national scale, which is an opinion of the credit risk of the issuer (or issue) compared to the creditworthiness of other issuers (issues) within a country and does not acknowledge the sovereign risk. Thus, national scale ratings (NSRs) cannot be used to compare the risk profile of companies located in different countries.[25] NRAs, GRAs and GRAs' subsidiaries and affiliates can offer NSRs. However, global scale ratings (GSRs) are only offered by GRAs, authorized GRAs' subsidiaries and IRAs. GRAs and IRAs can also offer regional scale ratings, which allows considering risk factors of a region.[26] NRAs can also offer regional scale ratings, but it is not common.[27] Literature shows that the NSRs assigned by GRAs or GRAs' affiliates are not comparable with the ratings assigned by NRAs (Jiang and Packer, 2019). Only one study in South Korea finds no statistically meaningful differences in the rating levels between affiliates of GRAs assigning local ratings and NRAs (Joe and Oh, 2017).

Ratings are also classified according to the type of issuer (e.g. bank, mutual fund, sovereign), type of obligation being rated (e.g. short or long term), and currency (foreign or domestic).[28] Not all CRAs offer the same type of ratings, some CRAs are specialized in given sectors (e.g. AM Best provides ratings for the insurance business).

At the global scale, GRAs and IRAs offer local currency and foreign currency ratings to issuers. These ratings can be compared internationally, but they differ in their definition. Foreign currency ratings assess the ability and willingness of the issuer to meet its financial obligations in foreign currency. They incorporate sovereign restrictions to currency transfers which could impact the issuers' capacity to meet debt service requirements in foreign obligations. Local currency rating is

---

[25] Is relevant to notice that the national rating scale does not acknowledge directly the sovereign risk, however, higher sovereign risk increases the risk assessed by the national scale's ratings.

[26] S&P has a regional rating scale that allow to compare ratings between countries of the region that is being rated. The regional ratings are: ASEAN Regional Scale (Association of South-East Asian Nations), Greater China Regional Scale (China, Hong Kong, Macau and Taiwan), and Gulf Cooperation Council Regional Scale (Gulf Cooperative Council countries). For Denmark, Finland and Sweden, there is a regional scale for short-term ratings (S&P, 2018a)

[27] Pacific Credit Ratings (PCR) is an NRA which operates in Peru but can also rate in Bolivia, Mexico, Costa Rica, Panamá, Ecuador, Guatemala, El Salvador, Honduras and Nicaragua. In addition to national scale ratings, PCR offers regional scale ratings (which covers México, Central America, Panama, Ecuador, Peru, Bolivia, and Dominican Republic) to issuers or issues which is valid in a certain economic zone that is under a commercial agreement (PCR, 2019).

[28] The description and examples presented in this section correspond to the long-term foreign currency issuer ratings, since the focus of this thesis is banks.

the assessment of the capacity and willingness of the issuer to meet its financial obligations in any currency, without considering the risk of facing government restrictions.[29]

GRAs and NRAs are a potential source of data and information on NSRs. However, when researching the determinants of NSRs and GSRs in Chapter 4, the NSRs assigned by NRAs are not included in the analysis for two reasons. Firstly, as one of the objectives of this thesis is to study both NSR and GSR assigned by the same CRA and the relationship between those NSR and GSR assignments, it is impossible to use NRAs because these CRAs do not offer GSRs. Secondly, the data on current NSRs assigned by NRAs is available from the NRAs' websites or the country's regulator of the credit rating industry. However, historical data is very difficult to collect, as it is typically not available from these sources. Alternatively, there may be a paid subscription service that is not available through Bangor University. In comparison, historical information on NSRs from GRAs is easier to access. For instance, S&P's NSRs are available from Interactive Data Credit Ratings in Emerging Markets (ID-CREM) provided by my supervisors and from CapitalIQ, a database from S&P accessed by subscription through Bangor University library. For Fitch and Moody's, data about NSRs is available on their websites and on GSRs is available on their websites and from ID-CREM.

Table 2.7, Panel A, presents an example of the long-term issuer rating based on the global and national rating scale.[30] The example includes the latest ratings of Banco Bilbao Vizcaya Argentaria (BBVA) from Spain (parent company) and BBVA subsidiaries operating in Uruguay, Colombia, Chile and Paraguay, and the latest ratings from two Colombian banks: Bancolombia and Banco de Bogota. In this particular example, the foreign and local long-term issuer ratings are the same, but it may not be the case in other issuers. Furthermore, because Panel A presents global scale ratings, it is possible to compare the ratings of BBVA (Parent Company) with its subsidiaries. In this example, BBVA Chile has superior credit quality than its parent company according to S&P and Fitch. Panel A also shows that the bank ratings are equal or lower than the sovereign ratings assigned by each GRA, except for the rating of BBVA Spain assigned by Moody's that exceeds the sovereign rating by two notches. Bank ratings in emerging economies are usually bounded by

[29] According to Capital Intelligence (2019), "Foreign currency ratings take into account the likelihood of a government imposing restrictions on the conversion of local currency to foreign currency or on the transfer of foreign currency to residents and non-residents". They also indicate that local currency ratings are "an opinion of an entity's ability and willingness to meet all of its financial obligations on a timely basis, regardless of the currency in which those obligations are denominated and absent transfer and convertibility restrictions. Both foreign currency and local currency ratings are internationally comparable assessments".
[30] Panel A of Table 2.7 shows that each GRA refers to the long-term issuer rating in a different way. S&P assigns long-term (foreign and local currency) ratings, Moody's the long-term counterparty risk rating (foreign and domestic) and Fitch assigns the long-term currency issuer default rating (foreign and local).

sovereign ratings, which has been called in the literature the “ceiling effect”(see Williams et al., 2013).

Table 2.7, Panel B, presents NSR assigned by S&P and by Fitch, because none of the banks in the sample have ratings assigned by Moody’s. Whereas Fitch does not assign GSR to BBVA Uruguay and Paraguay, Panel B shows that Fitch NSRs’ assignments are more than S&P NSRs’ assignments. Fitch assigned AAA at the national scale to BBVA Colombia and BBVA Chile. For investors, AAA indicates excellent credit quality compared to other peers in the same country, while global ratings are more relevant if investors are seeking for diversifying their international portfolio. However, the levels of GSR can affect the level of NSR. It is a common case in international financial conglomerates. For instance, in holding groups such as BBVA, subsidiaries are often required to transfer dividends or receive transfers or another type of support from the parent company. Thus, if the GSR from the parent company is downgraded, the rating change is likely to affect the global strategy of the holding group. In turn, this can have a significant effect on the subsidiaries’ business and even reduce the parents’ support and ultimately have a negative effect on the subsidiaries’ NSRs. Moreover, studies have shown that there is an interdependence between sovereign risk and bank risk (Williams et al., 2013). Moreover, bank risk increases when a sovereign crisis occur because banks can face limited access to funding or an increase in the cost (BIS, 2011; Correa and Sapriza, 2014). The transmission channels of sovereign distress to banks have been discussed from the perspective of credit ratings, however, the main focus has been on the global scale ratings, and there is no literature regarding the mechanisms of transmission of sovereign ratings to NSRs.

Table 2.8 presents an example of the notation of GSR (long-term issuer rating) and NSR (long-term issuer rating), using the rating scale categories of the three GRAs and HR Ratings, a Mexican IRA which is the only Latin American CRA registered with the SEC as an NRSRO and also certified by ESMA.[31] HR Ratings is selected for convenience because it assigns GSR and NSRs, however, other IRAs like DBRS also assign GSRs and NSRs. Generally, NSRs are identified by a two-letter prefix that corresponds to the country where the NSR is assigned. The definition of each rating category does not vary between a GSR and an NSR. The main difference between HR and the GRAs’ rating scales is the distinction between selective default and default (S&P) or lowest speculative ratings.

[31] HR Ratings obtains the status of NRSRO in 2007, while ESMA certifies HR Ratings in November 2014.

2.4 CRAs' business model

The credit rating industry operates under two revenue models, which can be chosen according to the preferences of the CRA. The first one is the issuer-pay business model, in which the issuer has to pay the CRA to rate its securities or its creditworthiness. The second one is the subscriber-pay business model, in which the subscribers pay a fee to access the credit ratings and the report issued by the CRA. The public-utility model is a third business model that states that the government should be in charge of providing ratings and ratings are quasi-public goods (Cinquegrana, 2009), however, only one CRA is known to operate using a mix of the public-utility model and the subscriber-pay business model in China (Hu et al., 2019). Ratings provided by CRAs (which use the issuer-pay) can be solicited or unsolicited. Solicited when CRAs have a contract with issuers, and issuers pay for ratings, and unsolicited when the ratings are issued by CRAs with public information and are not requested by the issuer; therefore, are not paid for.

The "public good nature" of the ratings and the free riding problems led to a change from the subscriber-pay model to an issuer-pay model in the 1970s (Camanho et al., 2012). However, some CRAs remain under the subscriber-pay model. GRAs operate under the issuer-pay business model. From the NRSRO list presented in Table 2.1, just EJ operates exclusively under the subscriber-pay model; Kroll Bond Rating Agency (KBRA) and Morningstar operate under both models but increasing the ratings under the issuer-pay model. Regarding the IRAs registered with ESMA[32], Table 2.2 shows that IRAs which operate under a mixed model are: Axesor S.A., Capital Intelligence (Cyprus) Ltd., Cerved Rating Agency S.p.A., ICAP Group SA and Spread Research. In addition, ModeFinance S.r.l. operates under the subscriber-pay model.

The implications of the compensation model on the quality of the ratings are one of the topics discussed in the academic literature. The issuer-pay business model has been criticized for the potential conflict of interest that derives from the relation between the issuer and CRAs (White, 2010). The size and relevance of the issuer have been addressed as a factor that influences ratings. Jiang et al. (2012) show that the bargaining power of large issuers influenced S&P ratings, especially when the GRA changed from the subscriber-pay model to the issuer-pay model. In comparison, a large number of academics assess positively the subscriber-pay model. For instance, Beaver et al. (2006) compare the features of bond ratings assigned by certified CRAs (by the SEC) against bond ratings assigned by non-certified CRAs. The study uses EJ, an IRA working under a subscriber-pay business model,[33] which was not approved by SEC at that time, and Moody's, showing that the ratings from EJ tend to lead the ratings from the latter GRA. Also, the study

[32] Egan-Jones Ratings Co. (EJ) and Kroll Bond Rating Agency (KBRA) are also registered with ESMA.
[33] See Section 2.1.3 for definitions of subscriber-pay vs. issuer-pay business models.

shows that the number of rating changes from EJ is higher than the number of Moody's rating changes, suggesting that the GRA is more conservative in their rating changes. Furthermore, the analysis of stock returns shows that the abnormal returns are higher for EJ than for Moody's, indicating that EJ assigns more informative ratings for the market. Thus, Beaver et al. (2006) argue that subscription-pay CRAs have more information content versus certified CRAs.

Chan et al. (2009) show that the subscription model in Australia offers aggregate value to investors, as the ratings assigned by these CRAs incorporate privilege information, not publicly available. Milidonis (2013) finds evidence that a subscriber-pay IRA, EJ, tends to lead S&P and Fitch in the US insurance industry because of the incentives of timely published ratings. Xia (2014) shows that S&P rating quality improves with the introduction of a subscribers-pay CRA, EJ, because of reputation concerns.

Further investigations of the certification as NRSRO and the compensation models show that the subscriber-pay model has a stronger effect on rating quality than the certification by the SEC (Bruno et al., 2016). The study examines the rating policy of EJ before and after acquiring the status of NRSRO against Moody's rating policy during the same period. The study finds EJ's rating changes lead Moody's rating changes before and after EJ's certification as NRSRO. Furthermore, Moody's ratings show a higher percentage of downgrades after assigning the initial rating while EJ shows more stability in their rating changes, indicating that Moody's ratings have an upward bias corrected in subsequent periods. Moreover, EJ's ratings do not converge to Moody's ratings after the certification, suggesting that EJ's ratings are driven by the subscriber-pay model instead of the certification effect.

The negative side of the subscription pay model is the free-riding dilemma, which is related to those investors, who are not subscribers but can access information without paying any fee. Deb et al. (2011) mention in their report that a more complex payment system is required to neutralize the negative aspects of both models (issuer-pay and subscriber-pay). Nevertheless, none of the payment models have changed and the credit rating business continues to be dominated by the issuer-pay model.

Regarding research on unsolicited ratings, the literature shows mixed findings. However, studies seem to agree that solicited ratings are far more informative than unsolicited ones. Bannier et al. (2010) analyse non-US firms for the period 1996 to 2006. They find that unsolicited ratings are downward biased compared to solicited ratings because CRAs tend to assign ratings in a more conservative manner when the rating is unsolicited and the issuer's opacity is high. Fulghieri et al. (2014) develop a theoretical model for unsolicited ratings under a monopoly industry. They find that CRAs produce unsolicited ratings to pressure the issuers to hire them and collect the rating fee. Moreover, they show that unsolicited ratings are normally associated with low quality firms. Hence, the lower level of those ratings compared to solicited ratings incorporate reputation concerns and can improve the investment-decision of the investors in low quality companies, as they try to diminish rating inflation. Byoun et al. (2014) suggest that unsolicited ratings have less information content than solicited ratings but do not find any downward bias. Therefore, they find that when rating changes occur, stocks only react to solicited ratings. Regarding the value of unsolicited ratings depending on the CRA's business model, Byoun (2014) develops a theoretical model, showing that under a subscriber-pay model, unsolicited ratings have the same information value than solicited ratings, while under an issuer-pay model, unsolicited ratings only show the low quality of the firms.

2.5 Conclusions

Chapter 2 provides an overview of the particular features of the credit rating industry based on the literature and the available information from CRAs. The investigation is divided into three topics: i) the composition of the credit rating industry, ii) the description of CRAs' rating scales, iii) the business model of CRAs.

The credit rating industry comprises three types of CRAs: i) GRAs, which operate worldwide and assign global, regional and national scale ratings, ii) IRAs which assign regional and national ratings and iii) NRAs which operate only domestically and assign only national ratings. The largest supervisors of the credit rating industry are the SEC for the US and ESMA for Europe. These supervisors regulate the rating practices of GRAs and IRAs. Each country has its own supervisors, who fulfill similar functions as the SEC and ESMA for NRAs. International CRAs offer global scale ratings and national scale ratings, while domestic CRAs (NRAs) only offer national ratings. Both global and national scale ratings offer long-term and short-term ratings to issuers, and global ratings usually are offered in foreign and local currency. The industry has two compensation models for the solicited ratings: an issuer-pay model and a subscriber-pay model. Each has advantages and drawbacks that have been studied by the credit rating literature.

Chapter 4 examines the determinants of national and global scale ratings assigned by S&P to banks from emerging economies. Chapter 5, the drivers of GRAs' rating disagreements in banks from emerging economies and the effects of those rating disagreements on future rating changes, and Chapter 6 investigates the relevance of the systematic component of those rating disagreements. Thus, the estimations in Chapter 4 incorporate the long-term foreign currency issuer rating (global scale rating) and long-term issuer rating (national scale rating) assigned by S&P. Chapters 5 and 6 examine the determinants of rating disagreements between GRAs. Hence, in those Chapters, the long-term foreign currency issuer rating from S&P, Fitch and Moody's is used in the estimations. The next Chapter presents a literature review of the studies relevant for this thesis, further complementing the outline of the credit rating industry developed in the current chapter.

Chapter 2 Tables

Table 2.1 CRAs registered with the SEC and recognized as NRSROs

Name	Location	Registration Date	Key business segment	Type of CRA[a]	Issues Unsolicited Rating (Y/N/ N/A)	Payment Model	Other registration[b]
S&P Global Ratings[c]	United States	24-Sep-2007	(i) through (v)	GRA	Y	Issuer-pay	ESMA
Moody's International Service	United States	24- Sep-2007	(i) through (v)	GRA	Y	Issuer-pay	ESMA
Fitch Rating Services	United States	24-Sep-2007	(i) through (v)	GRA	Y	Issuer-pay	ESMA
A.M. Best Company, Inc.	United States	24- Sep-2007	(ii), (iii), and (iv)	IRA	N	Issuer-pay	ESMA
DBRS, Inc.	United States	24- Sep-2007	(i) through (v)	IRA	Y	Issuer-pay	ESMA
Egan-Jones Ratings Company	United States	21-Dec-2007	(i) through (iii)	IRA	N/A	Subscriber-pay	ESMA
HR Ratings de México, S.A. de C.V.	Mexico	05-Nov-2012	(i), (iii), and (v)	IRA	Y	Issuer-pay	ESMA
Japan Credit Rating Agency, Ltd.	Japan	24-Sep-2007	(i), (ii), (iii), and (v)	IRA	Y	Issuer-pay	ESMA and ECAI
Kroll Bond Rating Agency, Inc.[d]	United States	11-Feb-2008	(i) through (v)	IRA	Y	Mixed	ECAI – NAIC
Morningstar Credit Ratings, LLC [e]	United States	23-Jun-2008	(i), (iii), and (iv)	IRA	Y	Mixed	No

The table reports the characteristics of the NRSROs registered with the SEC. Source: SEC Summary report of commission staff's examinations of each nationally recognized statistical rating organization (December 2014); SEC Annual Report on Nationally Recognized Statistical Rating Organizations (December 2018); ESMA; websites of the CRAs. Key business segment defined by the SEC: (i) financial institutions, brokers, or dealers; (ii) insurance companies; (iii) corporate issuers;(iv)issuers of asset-backed securities; (v) issuers of government securities, municipal securities, or securities issued by a foreign government; (vi) a combination of one or more categories of obligors described in any of clauses (i) through (v) above. ***a.*** *GRA: Global rating agency; IRAs: International rating agency.* ***b.*** *ECAI: External Credit Assessment Institutions. NAIC: National Association of Insurance Commissioners. ESMA: European Securities and Markets Authority* ***c.*** *Formerly known as Standard & Poor's Ratings Services* ***d.*** *Formerly known as LACE Financial Corp.* ***e.*** *Formerly known as Realpoint LLC.*

Table 2.2 CRAs registered and certified with ESMA

Name	Location	Status[a]	Registration Date	Key business segment	Type of CRA[b]	Unsolicited Rating[c]	Payment Model[d]
Euler Hermes Rating GmbH	Germany	R	16-Nov-10	Corporates, project finance and asset portfolio management	IRA	Y	IS
Japan Credit Rating Agency Ltd	Japan	C	06-Jan-11	Primary Japanese market - No ABS	IRA	Y	IS
BCRA-Credit Rating Agency AD	Bulgaria	R	06-Apr-11	Diversified	NRA	Y	IS
Creditreform Rating AG	Germany	R	18-May-11	Non-financial corporate, structured finance and covered bonds	NRA	N/A	IS
Scope Ratings AG	Germany	R	24-May-11	Diversified	IRA	Y	IS
ICAP Group SA	Greece	R	07-Jul-11	Non-financial and non- insurance institutions	NRA	Y	M
GBB-Rating Gesellschaft für Bonitätsbeurteilung GmbH	Germany	R	28-Jul-11	Banks, building societies, and leasing companies	NRA	Y	N/A
ASSEKURATA Assekuranz Rating-Agentur GmbH	Germany	R	18-Aug-11	Insurance industry	NRA	N	IS
ARC Ratings, S.A.[e]	Portugal	R	26-Aug-11	Diversified	IRA	Y	IS
AM Best Europe-Rating Services Ltd.	UK	R	08-Sep-11	Insurance industry	IRA	N	IS
DBRS Ratings Limited	UK	R	31-Oct-11	Diversified	IRA	Y	IS
CRIF Ratings S.r.l.[f]	Italy	R	22-Dec-11	Non-financial institutions based in the European Union	IRA	Y	IS
Capital Intelligence (Cyprus) Ltd	Cyprus	R	08-May-12	Diversified	IRA	Y	M
European Rating Agency, a.s.	Slovakia	R	30-Jul-12	Municipalities and non-financial institutions	IRA	Y	IS
Axesor SA	Spain	R	01-Oct-12	Diversified	IRA	Y	M
Cerved Rating Agency S.p.A.[g]	Italy	R	20-Dec-12	Non-financial institutions	NRA	N/A	M
Kroll Bond Rating Agency	USA	C	20-Mar-13	Structured finance	IRA	N/A	M

(Continued on next page)

Table 2.2 (continued)

Name	Location	Status[a]	Registration Date	Key business segment	Type of CRA[b]	Unsolicited Rating[c]	Payment Model[d]
The Economist Intelligence Unit Ltd	UK	R	03-Jun-13	Diversified	IRA	Y	SUBS
Dagong Europe Credit Rating Srl	Italy	R	13-Jun-13	Financial and non-financial institutions	IRA		IS
Spread Research	France	R	01-Jul-13	European SMEs, high yields and convertible bond issuers	IRA	Y	M
EuroRating Sp. z o.o.	Poland	R	07-May-14	Financial institutions and corporates	IRA	Y	IS
HR Ratings de México, S.A. de C.V.	Mexico	C	07-Nov-14	Diversified	IRA	N/A	IS
Egan-Jones Ratings Co.	USA	C	12-Dec-14	Diversified	IRA	N/A	SUBS
ModeFinance S.r.l.	Italy	R	10-Jul-15	Corporates	IRA	Y	SUBS
INC Rating Sp. z o.o.	Poland	R	27-Oct-15	Public sector entities	IRA	Y	N/A
Rating-Agentur Expert RA GmbH	Germany	R	01-Dec-15	Banks, corporates, insurance	IRA	Y	IS
Feri EuroRating Services AG[h]	Germany	DR	29-Mar-17	N/A	N/A	N/A	N/A
Kroll Bond Rating Agency Europe Limited	Ireland	R	13-Nov-17	Diversified	IRA	Y	IS
Nordic Credit Rating AS	Norway	R	03-Aug-18	Financial institutions and corporates	IRA	N/A	IS
SPMW Rating Sp. z o.o.[i]	Poland	DR	10-Oct-18	N/A	N/A	N/A	N/A
A.M. Best (EU) Rating Services B.V.	The Netherlands	R	03-Dec-18	Insurance industry	IRA	N	IS
DBRS Rating GmbH	Germany	R	14-Dec-18	Diversified	IRA	Y	IS
Beyond Ratings SAS	France	R	18-Mar-19	Public bond issuers. Planned: infrastructure bonds and utilities.	IRA	N/A	IS

The table reports the characteristics of the CRAs registered and certified with ESMA. Source: ESMA website (last update March 18th, 2019); websites of the CRAs. ***a****. R: Registered; C: Certified; DR: De- registered.* ***b****. IRA: International rating agency; NRA: National rating agency.* ***c.*** *Y: Yes, N: No, N/A: Not applicable or not available.* ***d.*** *IS: Issuer-pay; SUBS: Subscriber-pay; M: Mixed.* ***e.*** *ARC Ratings, S.A. was previously Companhia Portuguesa de Rating, S.A.* ***f.*** *CRIF Ratings S.r.l was previously CRIF S.p.a.* ***g.*** *Cerved Rating Agency S.p.A. was previously CERVED Group S.p.A.* ***h.*** *On 29Mar17 ESMA withdraw the registration of Feri EuroRating Services AG because it was acquired by Scope KGaA, the parent company of Scope Ratings on 01Aug16.* ***i.*** *SPMW withdraw the registration to ESMA on 30 August 2018.*

Table 2.3 GRAs and GRAs' subsidiaries registered and certified with ESMA

Name	Location	Status[a]	Registration Date
Fitch Deutschland GmbH	Germany	R	31-Oct-11
Fitch France S.A.S.	France	R	31-Oct-11
Fitch Italia S.p.A.	Italy	R	31-Oct-11
Fitch Polska S.A.	Poland	R	31-Oct-11
Fitch Ratings CIS Limited	UK	R	31-Oct-11
Fitch Ratings España S.A.U.	Spain	R	31-Oct-11
Fitch Ratings Limited	UK	R	31-Oct-11
Moody's Deutschland GmbH	Germany	R	31-Oct-11
Moody's France S.A.S.	France	R	31-Oct-11
Moody's Investors Service (Nordics) AB	Sweden	R	13-Aug-18
Moody's Investors Service Cyprus Ltd	Cyprus	R	31-Oct-11
Moody's Investors Service EMEA Ltd	UK	R	24-Nov-14
Moody's Investors Service España S.A.	Spain	R	31-Oct-11
Moody's Investors Service Ltd	UK	R	31-Oct-11
Moody's Italia S.r.l.	Italy	R	31-Oct-11
S&P Global Ratings Europe Limited[b]	Ireland	R	31-Oct-11
S&P Global Ratings France SAS	France	DR	20-Dec-18
S&P Global Ratings Italy S.r.l	Italy	DR	20-Dec-18

This table reports the GRAs and their subsidiaries register with ESMA. Source: ESMA (last update March 18th, 2019). ***a****. R: Registered; C: Certified: DR: De- registered.* ***b.*** *According to* S&P (2018b)*, until merging into S&P Global Ratings Europe Limited (SPGRE) during the course of 2018, S&P Global Ratings operated in the EU through Standard & Poor's Credit Market Services Europe Limited ("SPCMSE"); S&P Global Ratings France SAS ("SPGRF"); and S&P Global Ratings Italy SRL (SPGRI).*

Table 2.4 S&P subsidiaries

Name	Jurisdiction of Incorporation	Business Description	% Voting Securities Owned
S&P Global Australia Pty Ltd	Australia	Independent ratings, benchmarks, analytics	100.0
Standard & Poor's Ratings do Brasil Ltda	Brazil	Credit rating services	100.0
S&P Global Canada Corp.	Canada	Credit rating services	100.0
BRC Investor Services S.A.	Colombia	Credit rating services	100.0
S&P Global France SAS	France	Credit ratings, swap risk, mid-market evaluation, local government investment pools, principal stability, and counterparty instrument services.	100.0
Grupo Standard & Poor's S. de R.L. de C.V.	Mexico	Credit rating services	100.0
S&P India LLC	United States	Credit rating services	100.0
Standard & Poor's Financial Services LLC	United States	Market intelligence: credit ratings, indices, research.	100.0
Standard & Poor's International Services LLC	United States	Subsidiary of S&P Global, Inc. Credit rating services	100.0
Standard & Poor's International LLC	United States	Standard & Poor's International, LLC is a holding company	100.0
Standard & Poor's LLC	United States	Credit rating services	100.0
S&P Global Ratings Argentina S.R.L. Agente de Calificación de Riesgo	Argentina	Credit rating services	100.0
S&P Global Ratings Australia Pty Ltd	Australia	Credit rating services	100.0
S&P Global Ratings Chile Clasificadora de Riesgo Limitada	Chile	Credit rating services	100.0
S&P Global Ratings Management Service (Shanghai) Co. Ltd	China	Subsidiary of Standard & Poor's International, LLC	100.0
S&P Ratings (China) Co. Ltd.	China	Credit rating services	100.0
S&P Global Ratings Hong Kong Limited	Hong Kong	Credit rating services	100.0
S&P Global Ratings Europe Limited	Ireland	Credit rating services	100.0
S&P Global Ratings Maalot Ltd.	Israel	Credit rating services	100.0
S&P Global Ratings Japan Inc.	Japan	Credit rating services	100.0
S&P Global Ratings Singapore Pte. Ltd.	Singapore	Credit rating services	100.0
Crisil Irevna Argentina S.A.	Argentina	Subsidiary of Crisil Limited	67.1
CRISIL Limited	India	Ratings, data, research, and risk and policy advisory services	67.1
CRISIL Irevna US LLC Delaware	United States	Subsidiary of CRISIL Irevna UK Limited.	67.1
TRIS Rating Co. Ltd	Thailand	Credit rating services	51.6
Taiwan Ratings Corporation	Taiwan	Credit rating services	51.0
TRIS Corporation Limited	Thailand	Credit rating services	5.0

This table presents a list of the subsidiaries of S&P Global Inc. Source: S&P Global Inc. (August 9th, 2018); Business description from CapitalIQ; web pages of the subsidiaries and Bloomberg.

Table 2.5 Moody's subsidiaries, partnerships & alliances

***Panel A**. Moody's majority owned subsidiaries in the rating business*

Name	Location
ICRA Lanka Limited	Sri Lanka
ICRA Nepal Limited	Nepal
Moody's (China) Limited	China
Moody's (UK) Limited	UK
Moody's America Latina Ltda.	Brazil
Moody's Asia Pacific Group (Singapore) Pte. Ltd.	Singapore
Moody's Asia Pacific Ltd.	Hong Kong
Moody's Canada Inc.	Canada
Moody's China (B.V.I.) Limited	British Virgin Islands
Moody's Credit Ratings (China) Limited	China
Moody's de Mexico, S.A. de C.V., I.C.V	Mexico
Moody's Deutschland GmbH	Germany
Moody's Eastern Europe LLC	Russia
Moody's France SAS	France
Moody's Indonesia (B.V.I) Limited	British Virgin Islands
Moody's Investors Service (Beijing), Ltd.	China
Moody's Investors Service (BVI) Limited	British Virgin Islands
Moody's Investors Service (Korea) Inc.	Korea
Moody's Investors Service (Nordics) AB	Sweden
Moody's Investors Service Cyprus Ltd.	Cyprus
Moody's Investors Service EMEA Limited	UK
Moody's Investors Service Espana SA	Spain
Moody's Investors Service Hong Kong Ltd.	Hong Kong
Moody's Investors Service India Private Limited	India
Moody's Investors Service Limited	UK
Moody's Investors Service Middle East Limited	UAE
Moody's Investors Service Pty Limited	Australia
Moody's Investors Service Singapore Pte. Ltd.	Singapore
Moody's Investors Service South Africa (Pty) Limited	South Africa
Moody's Italia S.r.l.	Italy
Moody's Latin America Agente de Calificacion de Riesgo S.A.	Argentina
Moody's SF Japan K.K.	Japan
Moody's Investors Service, Inc.	United States (Delaware)
PT ICRA Indonesia	Indonesia

***Panel B.** Moody's Partnerships & Alliances*

Name	Location	Type of alliance	% Owned
China Cheng Xin Int. Credit Rating Co. Ltd.	China	Joint Venture	30%
Equilibrium Clasificadora de Riesgo S.A.	Peru and Panama	Affiliate	N/A
ICRA Limited		Subsidiary	Over 50%
Korea Investors Service, Inc (KIS)		Full Ownership	
Middle East Rating and Investors Service S.A.E. (MERIS)	Egypt	Joint venture	40%
Midroog Ltd.	Israel	Subsidiary	51%
ICR Chile[a]	Chile		49%

This table presents Moody's majority owned subsidiaries (Panel A), and Moody's partnerships and alliances (Panel B). Source Panel A: SEC FORM 10-K submitted by Moody's (February 22[th], 2019). Source Panel B: Moody's Investor service web page. ***a.*** *Through Equilibrium Holdings, Moody's owns 49% of ICR Chile.*

Table 2.6 Fitch Ratings affiliates

Names	Location
Fitch Australia PTY Limited	AU
Fitch Ratings Brasil LTDA	BR
Fitch Ratings (Beijing) Limited	CN
Fitch France	FR
Fitch Deutschland GmbH	DE
Fitch (Hong Kong) Limited	HK
Fitch Italia S.p.A.	IT
Fitch Ratings Japan Limited	JP
Fitch Mexico S.A. de C.V.	MX
Fitch Polska S.A.	PL
Fitch Ratings Singapore PTE Ltd	SG
Fitch Southern Africa (PTY) Limited	ZA
Fitch Ratings Espana S.A.	ES
Fitch Ratings Limited	UK
Fitch Ratings CIS Limited	UK and RU
Inter Arab Rating Company E.C.	BH
Fitch India Services Private Limited	IN
Fitch (China) Bohua Credit Ratings Ltd	CN
Fitch North Africa SA*	TU
Ram Holdings*	MY
Korea Ratings Corporation	KR
Pt Fitch Ratings Indonesia	ID
Fitch Holding S.A.	CL
Fitch Ratings (Thailand) Limited	TH
Fitch Peru*	PE
Aesa Ratings S.A. Calificadora De Riesgo*	BO
Fitch Venezuela, Sociedad Calificadora De Riesgo, S.A.	VE
Fix-Scr Argentina Calificadora De Riesgo S.A.*	AR and UR
Fix-Scr Uruguay Calificadora De Riesgo S.A.*	UR
Fitch Ratings Lanka Limited	LK
Fitch Centroamerica, S.A.	PA
Fitch Ratings Colombia, S.A. Sociedad Calificadora De Valores	CO
Fitch Costa Rica Califacadora De Riesgo, S.A.	CR
Fitch Centroamerica, S.A.	GT
Fitch Republica Dominicana S.R.L	DO

*This table reports Fitch Ratings' affiliates worldwide. Source: Fitch Ratings Annual NRSRO Certification (March 23rd, 2019) and Exhibit 4 of the document.*Minority owned by Fitch. AU: Australia; BR: Brazil; CN: China; FR: France; DE: Germany; HK: Hong Kong; IT: Italy: JP: Japan; MX: Mexico; PL: Poland; SG: Singapore; ZA: South Africa; ES: Spain; UK: United Kingdom; RU: Russia; BH: Bahrain; IN: India; TU: Tunisia; MY: Malaysia; KR: Korea; ID: Indonesia; CL: Chile, TH: Thailand, PE: Peru; BO: Bolivia; VE: Venezuela; AR: Argentina; UR: Uruguay; LK: Sri Lanka; PA: Panama; CO: Colombia; CR: Costa Rica; GT: Guatemala; DO: Dominican Republic.*

Table 2.7 Examples of GSRs and NSRs assigned by GRAs

Panel A. *Long-term (LT) foreign and local currency GSR*

Name	*S&P*			*Moody's*			*Fitch Ratings*			
	Foreign Currency LT	Local Currency LT	Date	LT Bank deposit rating (Foreign)	LT Bank deposit rating (Domestic)	Date	LT Foreign Currency Issuer Default Ratings	LT Local Currency Issuer Default Ratings	Date	Sovereign ratings[a]
BBVA Spain	A-	A-	06-Apr-18	A2	A2	29-Aug-18	A-	N/A	05-Dec-18	A-/Baa1/A-
BBVA Uruguay	BBB	BBB	07-Oct-15	N/A	N/A	N/A	N/A	N/A	N/A	BBB/Baa2/BBB-
BBVA Colombia	N/A	N/A	N/A	Baa1	Baa1	21-Dec-18	BBB+	BBB+	21-Jun-18	BBB-/Baa2/BBB
BBVA Chile	A	A	06-Jul-18	A3	A3	27-Jul-18	A+	A+	25-Mar-19	A+/A1/A
BBVA Paraguay	BB-	BB-	02-Mar-17	Baa3	Baa3	21-Jun-18	N/A	N/A	N/A	BB/Baa1/BB+
Bancolombia (CO)	BB+	BB+	12-Dec-17	Baa2	Baa2	11-Feb-19	BBB	BBB	21-Jun-18	BBB-/Baa2/BBB
Banco de Bogota (CO)	BB+	BB+	12-Dec-17	Baa2	Baa2	11-Feb-19	BBB	BBB	21-Jun-18	BBB-/Baa2/BBB

Panel B. *Long-term (LT) issuer NSR*

Name[b]	S&P		Fitch Ratings	
	LT debt issuer rating National scale	Date	LT debt issuer rating National scale	Date
BBVA Uruguay	N/A	N/A	N/A	N/A
BBVA Colombia	N/A	N/A	AAA(col)	02-Aug-18
BBVA Chile[c]	N/A	N/A	AAA(cl)	12-Jul-18
BBVA Paraguay	N/A	N/A	N/A	N/A
Bancolombia (CO)	AAA(col)	19-Mar-19	AAA(col)	21-Jun-18
Banco de Bogota (CO)	AAA(col)	25/09/2018	N/A	N/A

This table reports in Panel A, the Long-Term (LT) foreign and local currency issuer ratings of Banco Bilbao Vizcaya Argentaria (BBVA), BBVA subsidiaries in Uruguay, Colombia, Chile and Paraguay, and two banks from Colombia: Grupo Bancolombia and Banco de Bogota, assigned by S&P, Moody's and Fitch Ratings. Panel B reports the Long-Term (LT) issuer national scale ratings (NSR) to the same banks except BBVA, assigned by S&P, Moody's and Fitch Ratings. Source: websites of each GRA (last update: April 2019). CreditWatch or Outlook are omitted for the purpose of brevity. ***a.*** *Corresponds to the latest Long-Term (LT) foreign currency sovereign rating ordered: S&P/Moody's/Fitch Ratings.* ***b.*** *In this example, the selected banks do not have NSRs assigned by Moody's.*

Table 2.8 Comparison of the GSR and NSR of the Mexican IRA: HR Ratings

Equivalent LT issuer GSR				Equivalent LT issuer NSR			
HR	S&P	Moody's	Fitch	HR	S&P	Moody's	Fitch
Investment grade							
HR AAA (G)	AAA	Aaa	AAA	HR AAA	xxAAA	Aaa.n	AAA (xxx)
	AA+	Aa1	AA+		xxAA+	Aa1.n	AA+(xxx)
HR AA (G)	AA	Aa2	AA	HR AA	xxAA	Aa2.n	AA(xxx)
	AA-	Aa3	AA-		xxAA-	Aa3.n	AA-(xxx)
	A+	A1	A+		xxA+	A1.n	A+(xxx)
HR A (G)	A	A2	A	HR A	xxA	A2.n	A(xxx)
	A-	A3	A-		xxA-	A3.n	A-(xxx)
HR BBB (G)	BBB+	Baa1	BBB+	HR BBB	xxBBB+	Baa1.n	BBB+(xxx)
	BBB	Baa2	BBB		xxBBB	Baa2.n	BBB (xxx)
	BBB-	Baa3	BBB-		xxBBB-	Baa3.n	BBB-(xxx)
Speculative grade							
	BB+	Ba1	BB+		xxBB+	Ba1.n	BB+(xxx)
HR BB (G)	BB	Ba2	BB	HR BB	xxBB	Ba2.n	BB(xxx)
	BB-	Ba3	BB-		xxBB-	Ba3.n	BB-(xxx)
	B+	B1	B+		xxB+	B1.n	B+(xxx)
HR B (G)	B	B2	B	HR B	xxB	B2.n	B(xxx)
	B-	B3	B-		xxB-	B3.n	B-(xxx)
	CCC+	Caa1	CCC+		xxCCC+	Caa1.n	CCC+(xxx)
HR C (G)	CCC	Caa2	CCC	HR C	xxCCC	Caa2.n	CCC (xxx)
	CCC-	Caa3	CCC-		xxCCC-	Caa3.n	CCC-(xxx)
HR D (G)	CC, C	Ca, C	CC, C	HR D	xxCC, xxC	Ca.n	CC(xxx), C(xxx)
	SD and D	C	RD		xxD	C.n	RD(xxx)
	R		D		xxR		D(xxx)

This table reports the Long-term (LT) issuer NSR and GSR categories for HR Ratings, S&P, Moody's and Fitch. The rating scale of HR Ratings (GSR and NSR) can also have a plus (+) or minus (–) to show if it is close to the inferior or higher category (HR Ratings, 2019). *The 'xx' before the rating category in S&P NSR* (S&P, 2018a) *and the prefix 'n' after the rating category in Moody's NSR* (Moody's, 2019b) *denotes a two-letter prefix assigned to the country. Fitch NSR has an 'xxx' in parenthesis, which identifies the prefix of the country where the rating is assigned* (Fitch Ratings, 2018b).

Chapter 3 Literature review

3.1 Introduction

The main purpose of the current Chapter is to present the pertinent literature that supports the research questions formulated in each empirical chapter of the thesis. Section 3.2 presents the academic debate surrounding the benefits and pitfalls of the oligopolist structure of the credit rating industry, focusing on the role of S&P, Moody's and Fitch, the global rating agencies (GRAs), in the market and the importance of studying credit rating disagreements in the thesis. The section incorporates the available research on the certification effect of GRAs, herding behaviour, credit rating malpractices such as rating shopping and rating catering. Furthermore, the review of the literature on split ratings reveals that rating disagreements have a significant value for investors, as they are proxy of the uncertainty and the issuers' asset opacity perceived by GRAs. Moreover, the research shows that split ratings have a significant influence on rating migrations. The findings on split ratings are especially relevant for Chapters 5 and 6 of this thesis.

Section 3.3 presents the available research on the domestic rating business in emerging economies, which highlights the role of national rating agencies (NRAs) and the national ratings assigned by GRAs. The Section is divided into three parts: Section 3.3.1 presents a review of the literature on the economic impact of the credit rating business in emerging economies. The key finding is that credit rating agencies (CRAs) have a positive and significant influence on the development of the financial markets. Moreover, studies in Asia suggest that the credit rating industry is segmented between GRAs and NRAs, where the former are focused on rating large and international issuers and the latter in rating small domestic issuers. This argument is challenged in Chapter 4 of this thesis. Section 3.3.2 presents the available research on the credit rating business in Asian countries, showing that research on China and Korea has grown significantly due to the expansion of GRAs through affiliates and joint ventures. Section 3.3.3 reviews the studies on the domestic rating industry in other countries. It shows that the research on the topic is scarce, and the studies are mainly focused on NRAs from developed economies, while the research in emerging economies different from Asian countries is extremely rare and is mostly qualitative.

In sum, the review of the available research reveals the scarcity of credit rating literature in emerging economies and the particular dynamic of the rating business in these countries, where national scale ratings (from NRAs or GRAs) play an essential role in the market.

3.2 The value and impact of GRAs' credit ratings

GRAs' rating methodology stresses that credit ratings are opinions on the creditworthiness of an entity or debt obligation of the issuer, and as such, cannot be considered as investment advice or recommendation and cannot be used as a benchmark (S&P, 2011a; Fitch Ratings, 2018a; Moody's, 2018c). However, the overreliance on GRAs' ratings was noticeable during the U.S. subprime crisis (Deb et al., 2011; Bolton et al., 2012). Although there is evidence of less mechanistic market reactions to GRAs' sovereign rating actions with the introduction of a new regulator of CRAs in Europe during December 2009 (Alsakka et al., 2017), a substantial body of literature shows that the market still depends on GRAs' ratings due to the certification effect granted by regulators, with implications on GRAs' rating quality.

The certification effect has been a topic of theoretical and empirical academic literature, along with three other distortions associated with the competition among GRAs: i) rating shopping: when issuers hire multiple CRAs but only chooses the most convenient rating (Griffin et al., 2013); ii) rating catering: when CRAs' clients, who are a significant source of income for them, can exert pressure on the CRAs to get better ratings. As a result, CRAs shape the rating process to the clients' demands and may reduce the rating quality; iii) rating inflation: when the ratings are upward bias and do not reflect the level of risk exposure of the rated company.

3.2.1 Certification effect and reputation

CRAs can reduce the information asymmetries between the issuers and investors by providing information about the creditworthiness of the entity through their ratings. Moreover, the rating process also involves monitoring the rated companies, which also benefits investors by reducing the cost of monitoring and coordination (Boot et al., 2006). However, when ratings are required by regulation as part of financial contracts or investment requirements, rating actions can have a "certification effect" and influence excessively investors' decisions. The excessive reliance on credit ratings derived from regulation explains the adverse and pervasive effects of GRAs' downgrades on the capital markets observed during the subprime mortgage crisis (2007 – 2009) (IMF, 2010; Deb et al., 2011).

Academic theoretical literature shows that regulation which favours high rated securities can induce rating inflation, and the upward rating bias would be higher for high complexity assets (Opp et al., 2013). Kisgen and Strahan (2010) analyse the certification of Dominion Bond Rating Service (DBRS) as a Nationally Recognized Statistical Rating Organization (NRSRO). They find that regulation requirements, such as a minimum rating for investments, influence more investors than the certification of DBRS as an NRSRO. Hence, they find that the market did not perceive the status of NRSRO as an improvement in rating quality. Behr et al. (2016) find empirical evidence of rating inflation in U.S. corporate issuers after Moody's was approved as NRSRO by the U.S. Securities and Exchange Commission (SEC), showing that the rating inflation is more significant in the investment grade frontier. Moreover, the study shows that Moody's ratings are not upward bias because S&P switches from investor-pay (i.e. subscriber-pay) to the issuer-pay model in 1974.

GRAs argue that reputation concerns prevent them from assigning inflated ratings and perform the due process. Mathis et al. (2009) find that reputation is the main concern of GRAs only when the major source of income is assigning ratings to less complex (than mortgage-backed) securities. The research shows that when reputation is already gained, and investors trust GRAs, the rating decisions are not rigorous, especially when they are rating complex products, and during periods of economic stability. Moreover, studies show that reputation costs are not the only necessary condition for GRAs to avoid inflating the ratings when there are investors who have high confidence on GRAs and are less sophisticated (Bolton et al., 2012). GRAs' market reputation also seems to be less relevant when there is a strong business relationship with clients as shown by Efing and Hau (2015). In their study, they find evidence of inflated ratings for asset-backed securities (ABS) and mortgage-backed securities (MBS) assigned to GRAs' clients which have a relevant contribution to GRAs' rating fees. Moreover, they find that inflated ratings tend to occur during positive economic cycles because during those cycles GRAs have less reputational risk and fewer probabilities of default.

3.2.2 The role of competition on rating quality

By interviewing 14 market participants[34] from the UK between April and June 2005, Duff and Einig (2009) construct a theoretical framework about the process of receiving a rating. The study finds that the issuers' main determinant for selecting a CRA[35] is reputation. Hence, the interviewees declared to hold ratings from at least one GRA. The study indicates that the issuers' decision of hiring multiple CRAs usually obeys to regulatory requirements. However, it does not mention any distortions derivated from selecting multiple GRAs, thus, it does not cover aspects of rating shopping, the efficiency of the ratings and the model of payment, aspects that have been a matter of debate in academic literature and regulators (Spatt, 2009).

In a theoretical study, Camanho et al. (2012) find that under an issuer-pay model, the competition between CRAs can increase rating inflation, since the CRA would behave strategically to keep their market share, lowering the value of the ratings. As a consequence, the CRAs' reputation concerns are weaker when CRAs face lower profits under competition. However, the findings of the study are restricted as they work under the assumption of a duopoly credit rating industry (S&P and Moody's).

Rating shopping and the certification effect in the corporate bond market are examined by Bongaerts et al. (2012). The study shows that, when issues are rated by S&P and Moody's, the third rating from Fitch acts as a "Tie-breaker", preventing the adverse selection of issues with ratings near the speculative and investment grade frontier ("HY-IG boundary"). The study finds that Fitch ratings as tie-breaker supports partially the hypothesis of rating shopping and regulatory certification and does not show that Fitch ratings improve the information already contained in the ratings by the other two GRAs. However, the rating shopping hypothesis is only supported for issuers with ratings near the HY-IG boundary, who are more likely to seek a third rating, when they want to improve their credit assessment, as Fitch ratings seem to be over-optimistic compared to the rating of the other two GRAs. Since regulation requires to use the middle rating when an issuer is rated by three CRAs, for issuers near the HY-IG boundary, the third rating can determine if an issuer ends reporting an investment grade or speculative grade rating, supporting the regulation certification hypothesis. Becker and Milbourn (2011) also

[34] 9 corporate treasurers, 2 investors, 2 treasury consultants and a commercial banker.
[35] In Duff and Einig (2009), CRA refers to S&P, Moody's, Fitch, Dominion Bond Rating Services (DBRS) and A.M. Best.

investigate rating competition, finding that after Fitch is recognized as a GRA,[36] S&P and Moody's ratings showed an upward bias, which they suggest is to maintain their market share. The research shows that competition from a third GRA (Fitch), results in less reputation's concerns on the other GRAs, i.e. they produce less accurate ratings, diminishing the information quality of the ratings. However, they do not find strong evidence of rating shopping.

For the structured finance market, Skreta and Veldkamp (2009) develop a theoretical model focused on the issuers' behaviour. They show that issuers will look for one rating when they have assets with simple structures, as the market will perceive ratings as informative. As the asset becomes more complex, issuers will prefer to hire more than one CRA and disclosure the most convenient rating (one or both). Hence, higher asset complexity can exacerbate the probability of "rating shopping". However, they highlight that their theoretical model does not apply for highly complex structured finance products, because in those cases ratings do not transmit essential information to the market and represent an extra cost. Similarly, Bolton et al. (2012) find that GRAs' inflate their ratings when dealing with trustful investors and when their reputation is not at stake. Those trustful investors are pension funds and other investors whose profits are not linked to returns; in comparison, sophisticated investors are mutual funds and other investors whose income is linked to the investment returns. Moreover, they show that competition in the rating industry increases inefficiency in the market, as long as issuers can shop for the best rating. While their work shows the negative effects of competition under the presence of rating shopping, one of the model assumptions is that issuers can decide to pay or not the fee before the rating is published, an aspect that was eliminated through the Dodd-Frank act in 2010 and ESMA regulation.[37] .

Griffin et al. (2013) examine S&P and Moody's ratings for collateralized debt obligations (CDOs) and yield performance of CDOs before the subprime mortgage crisis. The study evaluates if the CDOs' rating signals released after the crisis are a result of rating catering, rating shopping or changes in the clients' business performance. They find that CDOs with dual ratings at the initial issuance underperform (default more often) than CDOS with individual ratings, which contradicts the rating shopping hypothesis. They also find

[36] Becker and Milbourn (2011) highlight the merger between Fitch and IBCA Limited in 1997 and the acquisition of Duff & Phelps and Thomson Bank Watch in 2000.
[37] Dodd-Frank act Section 932 (DFA, 2010) and the article 38 of the Regulation (EU) No 462/2013 of the European parliament and of the council of the European Union.

that GRAs usually assign the same rating as the competitor at the CDOs' issuance, however, the rating is usually adjusted in the subsequent period to reflect the accurate credit risk. Similarly, Griffin et al. (2013) show that the presence of rating catering when there are dual ratings reduces the information content of the ratings, therefore, affects the rating quality. In contrast, Morkoetter et al. (2017) find that competition between GRAs improves the informative role of ratings when examining U.S. MBS. However, they find that a third rating increases the uncertainty on the creditworthiness of the tranche. Furthermore, the study shows that investors have the incentive for rating shopping because rating level differences between GRAs are persistent in the long-run due to structural differences in their methodologies, and investors acknowledge which GRA is more conservative among them.

The empirical evidence shows that GRAs engage in rating shopping and rating catering practices when competing in the structured finance market, while the main problem of GRAs' competition in the financial and corporate markets appears to be rating inflation. Differences in the rating practices between markets could be related to the possibility of assigning unsolicited issuer ratings, which amplify GRAs' rating coverage, while in structured finance assigning unsolicited ratings is impossible due to the complexity of the products (Becker and Milbourn, 2011).

3.2.3 Herding behaviour

Theoretical academic literature shows that in the financial markets, agents can mimic the actions of other agents, displaying conduct denominated "herding behaviour" (Devenow and Welch, 1996). This study highlights that herding can be caused by payoff externalities (such as a bank run, or acquiring information), principal-agency problem decisions, or because a good investment decision by other investors overrides their own investment criteria (cascade). In the credit rating business, herding behaviour of the investors and cliff effects (a negative rating action leads to further negative response of the economy, amplifying the effect of the rating decision) of the CRAs have been tackled by regulators through strengthening CRA's regulations. In 2010, the Financial Stability Board (FSB) published the "Principles for Reducing Reliance on CRA Ratings", intending to "end the mechanistic reliance of ratings", by promoting independent credit analysis by market participants instead of relying only on the credit assessments by CRAs (Deb et al., 2011).

Herding behaviour among the CRAs is analysed by Lugo et al. (2015), showing that GRAs influence each other rating decisions on subprime MBS between 1992 and 2007, and the influence is correlated with the degree of market reputation. Fitch is the GRA with less influence, while S&P and Moody's have a higher reputation and hence, exert more influence. Accordingly, they find that when rating disagreements (split ratings) occur, Fitch is the GRA showing convergence to S&P and Moody's ratings.[38] Lugo et al. (2015) conclude that introducing new CRAs, to increase the competition, would not have any effect since the herding behaviour towards the CRA with the highest market reputation would appear. In the sovereign rating literature, Alsakka and ap Gwilym (2010b) find sovereign rating interdependencies between five CRAs[39] analysing the period between 1994 and 2009. They find that disagreements between CRAs are mostly of one or two notches. The study finds that Moody's and S&P lead the sovereign rating decisions while Fitch and the two Japanese IRAs included in the study, Japan Credit Rating Agency (JCR) and Japan Rating & Investment Information (R&I), are followers. In particular, Moody's tends to lead the rating upgrades; S&P tends to lead the downgrades and appears to be the most independent CRA. However, they find some evidence of leading behaviour in Japanese IRAs over Moody's, suggesting that their domestic expertise reflected in their qualitative assessments could explain the early rating reaction.

3.2.4 Split ratings

In credit rating literature, split ratings occur when two CRAs assign different ratings assigned to the same issuer (or issue) at the same time. Early studies have attributed rating disagreements to random errors in the rating process (Ederington, 1986). The random-error hypothesis states that split ratings are not related to different credit assessment between CRAs of the same risk category or to divergencies on the methodological approach and weights on the risk factors used by CRAs in their rating process but are related to unsystematic errors in the rating process, which are later corrected by the CRAs.

[38] Using a sample of non-financial and financial issuers rated by both Moody's and S&P during the period January 1994 to December 2005, Güttler (2011) finds that S&P tends to be timelier than Moody's in implementing rating changes. Moreover, Moody's ratings tend to converge to S&P ratings and not vice versa. Güttler (2011) finds stronger support for the case of rating downgrades than for upgrades.

[39] S&P, Moody's, Fitch, Japan Credit Rating Agency (JCR) and Japan Rating & Investment Information (R&I).

Ederington (1986) also shows that split ratings often occur in borderline rating categories, because in those categories there is a higher probability of error in predicting the credit risk of the rated entity.

Despite agreeing on the role of split ratings as an additional source of information for investors proposed by Ederington (1986), later studies refute the random-error hypothesis. Cantor and Packer (1997) examine rating disagreements between four rating agencies: Moody's, S&P, Fitch and Duff & Phelps Credit Rating Agency, and find that split ratings are caused by dissimilarities across CRAs in their rating criteria and rating scales. Morgan (2002) proposes the *opacity hypothesis* to explain split ratings. Examining initial ratings assigned by S&P and Moody's to financial and non-financial bonds in the US for the period 1983-1993, he finds that the banking industry has the highest number of split ratings, suggesting high levels of uncertainty. The study then tests if banks' financial features explain those rating differences, and shows that bank size, cash, loans, and trading assets significantly affect split ratings, while better capital reduces the uncertainty and split ratings. The results corroborate the opacity hypothesis: banks' asset opacity increases rating disagreements. Furthermore, the evidence of the study suggests that ratings are lopsided, namely, when split ratings occur, one GRA tends to assign lower ratings than the other. Between S&P and Moody's, the latter GRA tends to or behave in a more conservative manner in the ratings of the sample used in the study.

The opacity hypothesis is later tested using European bonds by Iannotta (2006) during the period 1993–2003, finding similar results regarding the high number of split ratings between Moody's and S&P in the banking sector, and the significant influence of asset opacity in split bank ratings. Contrary to Morgan (2002), the study finds a high number of split ratings among non-financial sectors, construction, and energy and utility. Iannotta (2006) differs from Morgan (2002) in the role of bank capital, as he finds that bank capital is a source of opacity. He explains that capital could be capturing the effect of omitted variables that are also a source of opacity and are not included in the study.

The influence of asset opacity is also found in split corporate ratings. Livingston et al. (2007) analyse the influence of asset opacity on US corporate bonds with split ratings by S&P and Moody's between 1983-2000. Besides financial characteristics, firm size and market to book ratio, the study uses as proxies of opacity, the number of analysts forecasting earnings per share (EPS), a ratio of forecasting EPS,[40] and the bid-ask spread of the corporates' stocks. Except for the bid-ask spread, they find that asset opacity proxies are a significant driver of split corporate ratings. They also find lopsided corporate ratings, with Moody's rating being the most conservative, consistent with Morgan (2002). Hyytinen and Pajarinen (2008) offer a different perspective of asset opacity and the effect on split corporate ratings, by analysing the determinants of split corporate ratings in small and medium size enterprises (SME) from Finland. The study finds that instead of bank size, the main driver of split ratings in SMEs is the number of years of the companies' operations. Specifically, corporates with few years of operation show more opacity than corporates with longer business trajectory. Bowe and Larik (2014) examine the determinants of split ratings for US corporates during the period 1995-2009. They find that financial characteristics, ownership structure, regulatory information accessibility,[41] and including an additional third rating (Fitch), have a significant influence on the probability of split ratings. It is worth noting that, unlike Morgan (2002) and Iannotta (2006), they find large corporates are less likely to be split rated.

Evidence of split ratings in emerging economies is presented by Ismail et al. (2015), who examine split corporate ratings between GRAs and NRAs from emerging and developed economies. They find that in emerging economies an optimal capital structure reduces the asymmetric information, which in turn reduces the corporate rating splits. However, this study presumes that NRAs and GRAs' rating scales are at the same level and omits the modifiers in the rating scale (+ and –) and just use the letter categories (e.g. use AA but not AA- or AA+), which can bias the findings. Vu et al. (2017) provide evidence supporting the opacity hypothesis using sovereign split ratings from emerging and developed economies. They find that the political risk proxies[42] have a significant influence on sovereign rating disagreements, especially for non-European countries. Moreover, they find that government transparency, measured by the Freedom of Information Act (FOIA), is a key determinant of sovereign split ratings between Moody's and Fitch in non-European emerging countries.

---

[40] The standard deviation of forecasted earnings per share divided by the stock price.

[41] Bowe and Larik (2014) incorporate a dummy variable that takes the value of 1 after the "regulation FD" enacted in 2000 by the SEC, which improves CRAs' access to the companies' private information.

[42] To proxy political risk, they use six worldwide governance indicators (WGI) published by the World Bank: Control of corruption, political stability and absence of violence, government effectiveness, voice and accountability, regulatory quality, and rule of law.

Differences in the impact of opacity on split ratings can be related to the definition of asset opacity as suggested by Dahiya et al. (2017). They examine if asset opacity is higher in the banking sector compared to non-banks using a set of nine measures of opacity.[43] They find mixed results: five proxies show that banks are more opaque than non-banks and four show the opposite. Furthermore, the study finds that the number of analysts giving their opinion on the future performance of the bank and liquidity[44] is the most accurate proxy of opacity. However, the study uses financial variables as controls, thereby, it does not shed light on the accuracy of those variables as proxies of asset opacity.

The literature also suggests that split ratings offer additional information on the uncertainly of the issuer (or issue). For US industrial bonds, Jewell and Livingston (1998) find that, when the bond has split ratings by S&P and Moody's, the average rating determines the bond yield. Moreover, they show that both ratings matter to investors and underwriters, independently of who rates lower or higher. Nevertheless, split ratings at the lower rating categories have the strongest effects on bond spreads. Livingston and Zhou (2010) show that investors acknowledge that corporate bonds with split ratings have higher uncertainty and, therefore, demand a higher yield premium than from bonds without split ratings. Further, Livingston and Zhou (2016) show that when bonds with split ratings between S&P and Moody's also have Fitch ratings (as a third GRA), the uncertainty caused by the split rating diminishes, and investors demand a lower premium compared to bonds with just split ratings by S&P and Moody's. For sovereign ratings, Vu et al. (2015) find that spreads react strongly when the GRA that assigned a lower rating in the previous period takes a negative action in the event period.

Previous studies also agree on the persistence of split ratings, which is also an additional argument against the random-error hypothesis by Ederington (1986). Livingston et al. (2007) find that corporate bonds remain with split ratings after four years of the initial issuance. Livingston et al. (2008) analyse the persistence of split ratings by S&P and Moody's using a sample of financial and non-financial bonds from the US in the period 1983-2000. They find that, in the sample, the majority of split ratings remain split ratings

[43] Dahiya et al. (2017) uses: i) market-based variables associated with the behaviour of the stock returns, ii) proxies of the analysts' opinion on the future bank performance, and iii) two measures of illiquidity.
[44] The measure of illiquidity is the average (over the fiscal year) of the ratio between the absolute daily return and the daily dollar volume of stocks from the banks and non-banks.

during the period of analysis. The persistence of the split corporate ratings is also reported by Bowe and Larik (2014), who estimate that approximately 55% to 65% of the corporates that have initial split ratings remain with split ratings for the next 10 years. Morkoetter et al. (2017) find that for U.S. residential mortgage-backed securities with split ratings at the issuance, the rating difference widens on the first three years after the issuance.

Issuers (or issues) with split ratings also have a higher probability of experiencing rating migrations. Livingston et al. (2008) analyse split ratings in bond issues from the US financial, industrial and utility sectors, and find that future rating migrations from S&P and Moody's are highly influenced by split ratings. They also show that, when bonds have split ratings, the GRA which assigns the superior (inferior) rating has a higher probability of downgrade (upgrade) the bond rating one year later. Likewise, Alsakka and ap Gwilym (2010b) show that sovereigns with split ratings have a higher probability of being upgraded (downgraded) after a year by the CRA that assigned the lower (higher) rating. As Livingston et al. (2008), they also find that larger rating differences (more than one notch split) increase the probability of a rating change. Alsakka et al. (2017) examine split sovereign ratings between GRAs in European countries, before and after the European Securities and Markets Authority (ESMA) started regulating European CRAs.[45] They find that S&P inferior ratings influence future rating downgrades by Fitch and Moody's, while Moody's lower ratings influence Fitch's negative future actions. The effect of S&P and Moody's rating disagreements on S&P rating changes is stronger after ESMA becomes the regulator of CRAs in the EU, while the link between split ratings between S&P and the other two GRAs gets weaker after ESMA.

Lugo et al. (2015) analyse rating disagreements between CRAs on the nonprime mortgage-backed securities during the period of the subprime crisis and find that split ratings ultimately lead to rating convergence. However, the time to revise the rating and reach rating convergence differ between GRAs. In their study, Moody's ratings converge to S&P's ratings, more than S&P converge to Moody's, while Fitch tends to be influenced by the other two GRAs and lacks influence on them. Hence, they conclude that the rating convergence is associated with GRA's market reputation. Park and Lee (2018) examine the rating convergence in Korean unsecured bond issuers, by focusing on the effects of

[45] The period before regulation is June 2006 to June 2011 and post-regulation from July 2011 to November 2014.

competition amongst three CRAs: Korea Ratings (KR), NICE Investors Service and Korea Investors Service (KIS). They find that hiring an additional third CRA (Korean firms are required to be rated at least by two CRAs), increases the likelihood of future rating upgrades by the other two GRAs. Hence, Park and Lee (2018) argue that competition[46] between CRAs in Korea has contributed to rating misbehaviour (rating shopping and catering), consistent with the findings by Becker and Milbourn (2011) for US industries.

[46] Park and Lee (2018) use the number of CRAs rating a company as proxy of competition.

3.3 The relevance of the domestic credit rating business in emerging economies

Emerging economies[47] are characterised by high information asymmetries, which are more significant than in developed economies (Ferri and Liu, 2005; Cisneros et al., 2012), and by low institutional transparency (Chen et al., 2015). These characteristics tend to hamper funding through the capital markets and favour the use of bank loans by borrowers (Nagano, 2018). Nevertheless, foreign capital flows have been increasing to emerging economies (Vo et al., 2017), supporting the growth of the bond market and the banking industry, and with this, stimulating the expansion of the credit rating business. As credit ratings contribute to decreasing the investors' cost of collecting and processing information and the monitoring costs (Boot et al., 2006), the role fulfilled by CRAs has been highly significant in the development of emerging economies. The current Section examines the literature on the domestic rating business, separating the role of GRAs, IRAs and NRAs and their influence in these economies.

3.3.1 The role of CRAs in emerging economies

Previous studies show that ratings from GRAs contribute to the development of the financial sector of emerging markets. Specifically, the sovereign ratings from GRAs have a significant impact on the financial system and play a relevant role in encouraging foreign portfolio investment (Kim and Wu, 2008). The sovereign bond spreads are also influenced by sovereign ratings from GRAs, which indicates that CRAs add value to the financial market of emerging economies (Cavallo et al., 2013). Furthermore, due to the weaker accounting standards observed in emerging economies, GRAs' corporate ratings have a certification effect on the financial reporting quality (Bae et al., 2013).

Literature suggests that higher information asymmetries and institutional environment bias the GRAs' sovereign credit assessments, assigning lower ratings in emerging economies. For instance, Ferri and Liu (2003) find that GRAs' corporate ratings in

[47] In this research the term "emerging economies" or "emerging markets" are based on the country classification in the World Economic Outlook (WEO) of the International Monetary Fund that divides the world into two major groups: i) advanced economies and ii) emerging market and developing economies (See Table 3.1). Moreover, is relevant to mention that South Korea is included as emerging market in the literature review due to its relevance in the credit rating research.

emerging economies are highly influenced by the sovereign ceiling,[48] while the corporate's own metrics are less relevant in the assigned rating. Thus, they argue that investors cannot distinguish between the corporate's own risk and the country-risk components in GRAs' corporate ratings in emerging economies. Further research on GRAs' ratings suggest that the high reliance on sovereign ratings, when rating non-financial institutions, explain the low investment of GRAs in collecting and processing information in countries that are not members of the Organisation for Economic Co-operation and Development (Non-OECD countries), compared to their investment effort in OECD countries (Ferri, 2004; Ferri and Liu, 2005). More recent studies show mixed evidence on the bias of GRAs when rating sovereigns in emerging economies. For instance, Amstad and Packer (2015) show that the bias found in previous research on GRAs' sovereign rating is not supported when they include determinants of credit risk. Namely, proxies of the macroeconomic, fiscal and institutional strength. In contrast, a literature review by Luitel et al. (2016), suggests that the lack of government transparency, weaker institutional environment, sensitivity to external shocks and low depth and high volatility in their capital markets are factors that explain the "foreign bias" of GRAs.

The research concerning the role fulfilled by other CRAs different from GRAs has sparkled recently, although it continues to be extremely limited. Generally, the literature suggests that NRAs contribute to financial development and hold valuable domestic knowledge. Ferri (2004) shows that NRAs' ratings are more informative for the market than GRAs' ratings because the former have higher domestic market penetration (measured by the number of analysts and the resources spent to gather information about the company). Ferri and Lacitignola (2010) analyse GRAs and NRAs' rating policy in a group of Asian economies[49] and find evidence of market segmentation. While GRAs are focused on rating larger firms listed in a foreign stock market, NRAs tend to concentrate

[48] Firms which are rated equal or above the sovereign ratings (sovereign ceiling) prior to a sovereign downgrade are more sensitive to rating downgrades after the sovereign rating decision, compared to firms which have a rating below the sovereign rating (Almeida et al., 2017). For bank ratings, Williams et al. (2013) find that banks rated at the same level as the sovereign rating are more sensitive to sovereign rating actions than banks with ratings lower than the sovereign rating. Furthermore, Huang and Shen (2015) provide evidence of the prevalence of a ceiling effect of sovereign ratings over bank fundamentals when GRAs (S&P and Fitch) assign bank ratings in non- high-income countries (NHIC).

[49] Japan, South Korea, India and Malaysia.

their ratings on small size domestic bond or equity issuers[50]. They suggest that the segmentation of the credit rating industry occurs because small companies prefer NRAs' high domestic knowledge and lower fees compared to GRAs, while larger size companies with globally-oriented business value GRAs' market reputation. Furthermore, by taking a sample of NRAs[51] operating in different countries,[52] they find that NRAs are relevant for the development of the financial markets, with a greater impact on the bond market. One of the explanations of the relative advantage of NRAs against GRAs in domestic markets proposed by Ferri and Lacitignola (2010) could also explain why GRAs incorporate NRAs as affiliates,[53] although regulatory restrictions can also influence the expansion of GRAs through affiliates and joint ventures (e.g China, South Korea). Marandola (2015, 2016) also shows that the presence of NRAs improves the development of the financial system by covering issuers that are not rated by GRAs and because their presence stimulates better banking regulations.

3.3.2 The credit rating business in Asia

The most extensive research in the credit rating literature focused on emerging markets is developed using Asian countries. According to Li et al. (2006), comparisons of Japanese CRAs with GRAs are more common than comparisons with other Asian CRAs, because Japanese CRAs have been in the market longer than the other CRAs, and because Japan has a large capital market, with a fast-growing debt market. The comparison between GRAs and Japanese CRAs could also be related to the presence of two IRAs with international operations: JCR and R&I, which have a competitive position in Japan and their ratings have similar coverage as GRAs (Packer, 2000).

In corporate ratings, previous studies suggest that GRAs and Japanese IRAs' ratings have a complementary role. Using an event study, Packer (2000) finds that GRAs' debt ratings

---

[50] According to Ferri and Lacitignola (2010), the type of ratings obtained by Asian companies and the size of those companies is collected from Bloomberg.

[51] Ferri and Lacitignola (2010) incorporate a dummy variable called NRA that takes the value of one if NRAs have a presence in the country. In the study, GRAs are included as NRAs when examining the presence of NRAs in the US.

[52] The sample includes CRA from: USA, India, Israel, Malaysia, Pakistan, Philippines, Portugal, South Korea, Taiwan, Thailand, Latin America (Argentina, Chile and Peru), Japan and South Africa. Although there is no detail of the CRA used, they highlight that USA refers to the three GRA.

[53] On November of 2007, Moody's publish a press release of the Technical Services Agreement between Moody's and the Peruvian CRA, Equilibrium, indicated that one of the main reasons of this action was "Equilibrium's local market knowledge".

and JCR and R&I's debt ratings are priced in the Japanese corporate bond spreads. Shin and Moore (2003) find that the keiretsu affiliation[54] of Japanese firms is not explaining the rating differences between JCR and R&I's ratings and GRAs' ratings, as the former IRAs show systematically higher ratings than the latter. Furthermore, the study shows that IRAs and GRAs' ratings have a high correlation, indicating a similar risk perception. While the study separates non-financial from financial ratings, one setback is that they cluster three types of financial ratings (issuer, issue and financial strength) to estimate their models. By definition, issuer and issue ratings evaluate the creditworthiness of the issuer or issue, however, financial strength is used for the insurance sector and asses the capacity to pay under its insurance policies and do not include the debts held by the insurance company.

Li et al. (2006) find that GRAs' downgrades of the Japanese financial firms have a stronger impact than R&I and JCR's downgrades on the Japanese stock market, independently of which GRA assigns the rating. Although the study does not indicate the size of the companies rated by GRAs vs. the ones rated by both IRAs, the effect on the stock market could be showing the credit industry specialization observed in Asia (see Ferri and Lacitignola, 2010), whereby GRAs are focused on rating larger size companies. Thus, GRAs' ratings could be generating a stronger impact on the stock market than rating changes of SME companies.

Han et al. (2012) show that Japanese corporate firms prefer to hire GRAs instead of IRAs because, despite the lower level of ratings, GRAs tend to diminish issuing costs and reduce information asymmetries, increasing the firms' chances of successful bond issue placement. Nevertheless, the study finds that during the financial crisis period (January 2008 to March 2009) bonds rated by GRAs did not trade at a lower yield than those rated by IRAs; therefore, the reputation benefit weakened during that period. Moreover, the study highlights that firms with better financial performance (e.g. higher profitability measured by the return on assets - ROA) and less international influence (e.g. foreign ownership, global bond issues) seek for IRAs' ratings instead of GRAs. Hence, GRAs would be adding value to the Japanese bond issues not through the ratings but through their reputation (called certification effect in the study), and IRAs would be showing the "true value" of the domestic bond issues in Japan.

[54] Keiretsu affiliation is a type of Japanese corporate organization, were the firms have shared shareholders between the companies of the group and have strong ties with financial institutions.

In China, Poon and Chan (2008) find relevant information contained in the downgrade actions of Xinhua-Far East, an independent NRA located in China, although the study recognizes that the NRA is biased towards positive ratings. Jiang and Packer (2017) investigate the drivers of the difference in the corporate bond ratings assigned by Chinese NRAs against GRAs, [55] finding that that corporates with larger size and higher leverage are more likely to have a higher rating by NRAs, while higher profitability and state-ownership increases the probability of having higher ratings by GRAs. Livingston et al. (2018) examine the effect of ratings from Chinese NRAs in the yield spreads of Chinese corporate bonds. They show that both ratings from Chinese NRAs and from Chinese NRAs affiliated to GRAs are priced by investors, although the magnitude of the spread of a notch-difference in the ratings of each type of NRA differ, suggesting that the rating scale is not comparable. Jiang and Packer (2019) examine the Chinese NRAs and GRAs and also find an impact of the ratings of both in the market prices despite having significant differences in the rating scales. Hu et al. (2019) examine the quality of issuer-national ratings in non-financial institutions before and after China Bond Rating (CBR), an NRA operating under a mix between a subscriber-paid model and public utility model[56], which started operations in 2010. They show that companies rated by both CBR and other NRAs decreased the ratings compared to companies rated only by the other NRAs. Specifically, CBR induced more conservative rating behaviour in NRAs in partnerships with GRAs. Moreover, using an event study, they find that the market reaction to downgrades from CBR is negative and highly significant. In sum, Hu et al. (2019) suggest that the activity of CBR improved the rating quality of the credit rating industry in China.

Han et al. (2009) extends Li et al. (2006) investigation to other Asian countries,[57] and incorporate corporate ratings assigned by Asian NRAs[58] versus S&P and Moody's from 1990 to 2006. The sample is divided between Korea Investors Service (KIS) and the rest of NRAs because KIS has more than 60% of the rating changes. The analysis shows that

[55] To compare global scale ratings by GRAs with the national ratings from NRAs they perform a rating transformation to align the rating levels. The transformation involves ranking the Chinese domestic ratings and assign a rating that follows the order of the GRAs' rating scale.
[56] Refers to
[57] Taiwan, Malaysia, India, Indonesia, Thailand, Philippines, China and South Korea.
[58] Taiwan Ratings Corp (TRC), RAM Ratings Services (RAM), Credit Rating Information Services of India (CRISIL), PEFINDO in Indonesia, Korea Investors Service (KIS), Thai Rating and Information Services (TRIS), Philippine Rating Services (PHIL) and XINHUA in China.

among NRAs, only KIS is more influential than the two GRAs. Nevertheless, the findings have to be taken cautiously, as KIS has been a majority-owned affiliate of Moody's since 2001. Considering the affiliation, none of the independent NRAs would be influential in the corporate market relative to GRAs. Ferri et al. (2013) examine the Korean market reaction to the ratings from the National Information & Credit Evaluation (NICE), an independent Korean NRA, with the ratings from KIS (affiliated to Moody's) and Korea Ratings (KR) (affiliated to Standard and Poor's). Using an event study, Ferri et al. (2013) find that the price movements of Korean corporate bonds are more influenced by ratings assigned by NICE than by KIS or KR. They argue that NICE has more market credibility than KIS and KR because their inside knowledge of the Korean market is more valued in the domestic market than GRAs' reputation. The growth and influence of NICE might also be explained because GRAs operate through their NRAs affiliates in Korea and not directly through subsidiaries. Park and Lee (2018) show evidence of rating shopping and rating catering in the bond ratings assigned by the largest Korean NRAs: KIS, KR and NICE. The probability that an issuer terminates the contract with one of those NRAs is lower if they receive a higher rating from that NRA compare to the ratings assigned by the other NRAs. Furthermore, all three NRAs are more likely to upgrade (downgrade) a corporate bond when the rival NRA has assigned a higher (lower) rating.

Todhanakasem (2001) points out that independent NRAs in Thailand, have encountered several limitations to expand their business, such as cultural barriers (fear to disclose information), lack of quality of the information reported to the NRA and low requirements about the information disclosure for regulators. Moreover, the study indicates that the small size of the capital market influences the capacity of the NRA to develop its methodologies.

3.3.3 The credit rating business in other countries

The literature on the credit rating industry in the US examines the lead-lag behaviour of IRAs versus GRAs, and also the impact of compensation models in the rating behaviour. For instance, Beaver et al. (2006) show that ratings from Egan-Jones (EJ), an IRA working under a subscriber-pay business model,[59] are timelier, hence, more informative for investors, compared to ratings from issuer-pay CRAs. Moreover, they find that the

[59] See Section 2.1.3 for definitions of subscriber-pay vs. issuer-pay business models.

CRAs that apply the issuer-pay model tend to be more conservative when taking rating changes. Milidonis (2013) finds that bond rating changes by Egan Jones Ratings (EJ) lead GRAs' bond rating changes in the US insurance sector. The study attributes the results to the stronger incentive that EJ has to provide more accurate and timely ratings compared to GRAs because their rating fee comes from the investors (who rely on ratings in their investment decisions) and not from the issuers. Likewise, Milidonis (2013) finds that EJ's rating announcements have significant economic value and they have a larger impact on the bond market than GRAs' announcements. Similarly, Bruno et al. (2016) find that EJ's rating changes lead to Moody's rating changes before and after EJ certification as NRSRO. They also find that after the certification, EJ rating policy remains the same, suggesting that their ratings are driven by the subscriber-pay model instead of the certification effect.

Studies on NRAs in Israel are focused on Midroog, a majority-owned subsidiary from Moody's, and Maalot, a wholly-owned subsidiary from S&P. Both Midroog and Maalot are considered NRAs in this thesis since they operate with their own rating methodologies instead of GRAs' rating methodologies. Bakalyar and Galil (2014) examine the operation of Midroog and Maalot, finding that Maalot's ratings are inflated due to rating shopping, and Midroog's ratings reflect differences in the rating scale. They also reveal particular characteristics of Israel's rating market, such as the low number of bond issues and the absence of unsolicited ratings, which can encourage rating shopping practices. However, the study presents strong assumptions and generalizations, which might bias the results. For instance, differences in the rating methodologies of each NRA are not acknowledged in their study, assuming that both NRAs assess the same risk factors in the rated companies. They also do not consider Israel's economic framework, the economic perspective of each GRA, and the goodness of fit of the selected financial variables to predict the rating, casting doubts on the estimation of the shadow ratings. Furthermore, the study does not consider the certification effect or reputation of the NRAs, which could be an additional explanation for firms with single ratings.

The rating announcements of Midroog and Maalot in Israel are also analysed by Afik et al. (2014). They examine the effect of corporate rating actions by both NRAs on Israel's stock and bond returns and find that the information provided by both NRAs' actions is anticipated by the market. Their rating upgrades do not have any significant effect, while their downgrades have limited influence on Israel's equity and bond markets. Similar to

Bakalyar and Galil's (2014) findings, they suggest that the small size of the corporate market, the lack of unsolicited ratings and low debt rated by NRA promotes rating shopping, with corporate issuers selecting which NRA would rate them.

Chan et al. (2009) compare the effect on stock returns of rating changes of one NRA (Corporate Scorecard Group), which operates under the subscription-paid model in Australia, against rating changes by Moody's. Whereas Corporate Scorecard Group is specialised in rating small firms, Moody's tends to assign ratings to larger firms. The NRA benefits subscribers by providing additional information not available to the public, while Moody's ratings incorporate only public information. Hence, the ratings by Corporate Scorecard Group are more informative in the Australian stock market.

Empirical studies on the credit industry in Latin America[60] examine only GRAs, without including other CRAs. For Uruguay, Borraz et al. (2011) show that Uruguay's economic fundamentals have improved over time (from 2000 to 2010), however, they are not reflected in the sovereign ratings by S&P and Moody's. Therefore, they cast doubts on the GRAs' non-investment condition of Uruguay. Avendaño and Nieto-Parra (2015) examine the determinant of the costs of corporate bonds issued in the international market for 43 emerging markets. They show that underwriting fees are affected by GRAs' ratings, while the effect of GRAs' rating on the primary bond spreads is weak. Thus, they conclude that bond spreads are mostly affected by the sovereign credit rating through the sovereign ceiling effect. Nogueira and Fonseca (2013) show evidence of a strong negative impact of rating downgrades by GRAs of publicly traded companies on the stock markets of Brazil, Mexico, Chile and Argentina. Bone and Ribeiro (2009) find little evidence of the informational value of corporate ratings by Moody's in the Brazilian stock market, however, the effect of initial ratings is stronger, and the economic shocks seem to have more relevance to explain the corporates' risk.

Research on the dynamics of GRAs and NRAs in Latin America are scarce, and often descriptive. Cisneros et al. (2012) describe the role of GRAs and NRAs in Peru as crucial to diminish information asymmetries in the country and to support the local market development. Juambeltz (2014) reviews the role of CRAs in Uruguay, focusing on GRAs' sovereign rating methodology. He compares the evolution of Uruguay's sovereign rating compared to the sovereign ratings assigned by GRAs in other emerging economies and

---

[60] See Table 3.1 for the list of emerging and developing countries classified as Latin America and the Caribbean.

highlights that GRAs' sovereign ratings are the ceiling of GRAs' national ratings. Marandola (2016) incorporates Latin American countries when building a dataset of worldwide NRAs. She finds that Asia and Latin America are the regions with the highest number of NRAs because the government has encouraged their operation as a strategy to stimulate financial development.

3.4 Conclusions

In the US and Europe, the credit rating industry is dominated by GRAs. Their ratings represent more than 95% of the total ratings assigned by regulated CRAs. The oligopolistic structure of the industry and the overreliance of market participants on GRAs' ratings have prompted the academic interest in GRAs' rating practices. Research often criticises the certification role granted by financial regulators to registered CRAs, showing that those CRAs (and mainly the GRAs) have become less concerned about their reputation and more aware of their market power, relaxing their rating quality. Empirical evidence shows that rating inflation, herding behaviour, rating shopping, and rating catering are the negative outcomes associated with GRAs' competition.

The investigations of GRAs' rating disagreements suggest that they have a significant connection with opacity. Empirical evidence shows that large differences in bond ratings assigned by different CRAs are interpreted by investors as a signal of high opacity, thereby demanding higher opacity premiums. Moreover, GRAs' rating disagreements can influence future rating changes. The literature on split ratings is primarily focused on corporates, and less extensive on sovereign ratings and structured securities. Studies on split ratings on the financial sector are scarce and cover only banks from the US and the EU. Furthermore, investigations on split bank ratings in emerging economies are absent from the literature. Some possible explanations for the lack of research in these countries could be deficiencies in the quality of information, low data standardisation and lack of reporting.

Despite the extensive research on GRAs' rating practices, the available research examines GRAs' global scale ratings, and none incorporate GRAs' national scale rating in the analysis, except when discussing NRAs affiliated or in partnerships with GRAs. Investigations on domestic ratings usually cover only the remaining CRAs, are extremely scarce and mainly consist of cases of study, mostly from Asian countries. They show that in emerging economies the credit rating industry is segmented. GRAs and IRAs rate large companies while NRAs rate SME. The competition between NRAs and GRAs is addressed scarcely in the literature by comparing GRAs' global ratings with NRAs' domestic ratings (Ferri et al., 2013; Jiang and Packer, 2019). Livingston et al. (2018) examine domestic ratings assigned by GRAs' affiliates and NRAs in the corporate and financial sector of China but does not include GRAs or their domestic ratings. Because the literature is silent on the investigation of GRAs' national ratings, to study the drivers of the rating requests to GRAs in both scales (global and national) can contribute to understanding the importance of GRAs' national ratings in emerging economies.

Considering the potential limitations of information in emerging economies, examining split bank ratings in these countries is a matter worth to examine for several reasons. Firstly, bank opacity hinders the ability of regulators to improve market discipline and increases the likelihood of contagion effects when the financial system is in distress, leading to higher systemic risk. Therefore, the effects of bank opacity become even more relevant in emerging economies, characterised by high information asymmetry, weak institutional framework and government opacity. However, higher uncertainty and less transparency in emerging economies can diminish the information content of bank rating disagreements, which would indicate that the *asset opacity hypothesis* does not apply to banks in emerging economies. To sum, findings on split bank ratings in emerging economies can provide an insight into the effect of asset and government opacity. The findings can disentangle how efficient are bank regulations in emerging economies and how much influence has information asymmetry on rating disagreements. Thirdly, the study of the impact of split ratings on rating migrations in emerging economies is a topic that has been investigated in sovereign and corporate ratings, while there is no known evidence of the investigation of the topic in the banking industry, which can also contribute to clarifying the interdependencies and competition between GRAs in emerging economies.

From the literature review, the empirical chapters of the thesis examine those aspects absent or scarcely studied by academics. Chapter 4 addresses the interdependencies between national and global ratings from S&P. In particular, the interrelation of initial rating requests in national scale ratings and global scale ratings from S&P in banks from emerging economies, and the determinants of those rating requests. Chapter 5 examines the determinants of split bank ratings from all three GRAs and tests the lopsided hypothesis. Additionally, it addresses the impact of split bank ratings on future bank rating changes. Chapter 6 discusses the systematic component of split bank ratings under conditions of asset opacity and the ceiling effect of sovereign ratings.

It is relevant to notice that the current study has the limitations encountered by previous studies using data collected from emerging economies, namely, lack of uniformity on the periods reported by banks. Although this aspect can limit the ability to address gaps in the literature of national scale ratings, they are addressed in the development of this thesis.

Chapter 3 Tables

Table 3.1 List of emerging and developing economies by region

Commonwealth of Independent States	**Emerging and developing Europe**	**Latin America and the Caribbean**	**Middle East, North Africa, Afghanistan, and Pakistan**	**Sub-Saharan Africa**	
Armenia	Albania	Antigua and Barbuda	Afghanistan	Angola	Seychelles
Azerbaijan	Bosnia - Herzegovina	Argentina	Algeria	Benin	Sierra Leone
Belarus	Bulgaria	Aruba	Bahrain	Botswana	South Africa
Georgia	Croatia	The Bahamas	Djibouti	Burkina Faso	South Sudan
Kazakhstan	Hungary	Barbados	Egypt	Burundi	Tanzania
Kyrgyz Republic	Kosovo	Belize	Iran	Cabo Verde	Togo
Moldova	FYR Macedonia	Bolivia	Iraq	Cameroon	Uganda
Russia	Montenegro	Brazil	Jordan	Central African Republic	Zambia
Tajikistan	Poland	Chile	Kuwait	Chad	Zimbabwe
Turkmenistan	Romania	Colombia	Lebanon	Comoros	
Ukraine	Serbia	Costa Rica	Libya	Democratic Republic of the Congo	
Uzbekistan	Turkey	Dominica	Mauritania	Republic of Congo	
	Guyana	Dominican Republic	Morocco	Côte d’Ivoire	
	Haiti	Ecuador	Oman	Equatorial Guinea	
Emerging and developing Asia		El Salvador	Pakistan	Eritrea	
Bangladesh	Samoa	Grenada	Qatar	Eswatini	
Bhutan	Solomon Islands	Guatemala	Saudi Arabia	Ethiopia	
Brunei Darussalam	Sri Lanka	Guyana	Somalia	Gabon	
Cambodia	Thailand	Haiti	Sudan	The Gambia	
China	Timor-Leste	Honduras	Syria	Ghana	
Fiji	Tonga	Jamaica	Tunisia	Guinea	
India	Tuvalu	Mexico	United Arab Emirates	Guinea-Bissau	
Indonesia	Vanuatu	Nicaragua	Yemen	Kenya	
Kiribati	Vietnam	Panama	Afghanistan	Lesotho	
Lao P.D.R.		Paraguay	Algeria	Liberia	
Malaysia		Peru	Bahrain	Madagascar	
Maldives		St. Kitts and Nevis	Djibouti	Malawi	
Marshall Islands		St. Lucia	Egypt	Mali	
Micronesia		St. Vincent and the	Iran	Mauritius	
Mongolia		Grenadines	Iraq	Mozambique	
Myanmar		Suriname	Jordan	Namibia	
Nauru		Trinidad and Tobago	Kuwait	Niger	
Nepal		Uruguay	Lebanon	Nigeria	
Palau		Venezuela	Libya	Rwanda	
Papua New Guinea			Mauritania	São Tomé and Príncipe	
Philippines			Morocco	Senegal	

This table presents the classification of emerging and developing economies by region. Source: IMF (2018). This classification does not account for: Anguilla, Cuba, Republic of Korea, and Montserrat because those countries are not IMF members. Somalia is also not included in the emerging market and developing economies group because of its data limitations.

Chapter 4 Banks' rating assignments in emerging economies: A new perspective

BANGOR UNIVERSITY

4.1 Introduction

In emerging economies, the presence of Global Rating Agencies (GRAs) is closely associated with the level of development of the financial system, the transparency and strength of the institutional environment and the demand for credit ratings. Since the presence of National Rating Agencies (NRAs) is an indicator of the development of the financial and institutional environment and the credit rating industry, GRAs tend to commence operations only after the country has well-established NRAs (Marandola, 2015, 2016). As GRAs can assign national scale ratings and NRAs have a strong presence in emerging economies, GRAs are potential competitors of NRAs in the assignment of national ratings. Research on national ratings has seen an awakening of research in recent years, although is very scarce and consists mainly of country-specific studies in Asian countries (Ferri et al., 2013; Jiang and Packer, 2017, 2019; Joe and Oh, 2017; Yang et al., 2017; Livingston et al., 2018; Hu et al., 2019; Oh and Kim, 2019). These studies reveal mixed evidence regarding the reputational capital of GRAs versus NRAs, yet they highlight that ratings from both types of credit rating agencies (CRAs) have a significant (although different) value for market participants. One plausible reason for this is that emerging economies are characterised by high information asymmetry and weak institutional environment. These issues limit market participants' access to information on good quality. Thus, both ratings from NRAs and GRAs bridge the information gap between issuers and market participants.

The effect of national scale ratings (NSR) and global scale ratings (GSR) assigned by GRAs in emerging economies has been analysed separately by the credit rating literature. For instance, Ferri and Lacitignola (2010) find a segmentation in the credit rating industry of Asian countries, with GRAs assigning ratings to large and international companies while NRAs rate small domestic companies. This argument of segmentation is challenged by Jiang and Packer (2017), who identify that large companies in China are more likely to receive higher ratings from NRAs than from GRAs. Thus, large (small) companies may benefit more from ratings assigned by NRAs (GRAs). The available literature (e.g. Ferri and Lacitignola, 2010; Marandola, 2015, 2016) however, disregards the feature that companies can have both GSR and NSR assigned by GRAs. This could be preferable from the issuer standpoint because of the greater potential reputational value of GRAs' ratings.

This Chapter addresses the gap in the literature by examining the determinants of rating (global or national) assignments by S&P to banks from emerging economies. Furthermore, as rated banks can merge, expand, issue bonds or equity in foreign currency, and face other lifecycle events, it is reasonable to consider that bank ratings also evolve with these changes. Thus, instead of a static process between assigning NSRs or GSRs, this Chapter argues that there is a relationship between those two types of ratings. NSRs can complement GSRs, or GRAs can assign first an NSR and then assign a GSR (or vice versa) depending on their assessment of the effect of the mentioned changes on the bank's risk profile or simply to comply with new regulations (e.g. when issuing bonds overseas). Five sub-hypotheses that test the dynamic between global and national ratings are developed in this Chapter (see Section 4.3).

In the past ten years, the expansion of the credit rating industry in emerging economies has been closely tied to any country-specific growth in firms' bond issuance (e.g. see Jiang and Packer, 2017, 2019; Livingston et al., 2018; Hu et al., 2019). Thus, the presence of GRAs in these countries is partially explained by a larger size of the emerging bond markets and thereby a strong demand for credit ratings, related to the presence of NRAs and tighter banking regulation (Marandola, 2016). Moreover, the expansion in emerging economies is also part of the GRAs' strategy to diversify their revenues and to expand their business. For instance, Moody's acknowledges emerging economies as part of their "key growth drivers" (Moody's, 2018a; pp. 11), while S&P incorporates the expansion to the Chinese market in their strategic plan for 2019 (see S&P Global, 2019).

Strong information asymmetries in emerging economies constrain firms' access to the capital markets and divert funding demands to bank loans (Nagano, 2018). Thus, despite the growth of the capital markets, the banking sector continues to have a highly significant role in these economies. The systemic importance of the banking sector and the high amount of international capital inflows to emerging economies as portfolio and direct investment (Williams et al., 2015; Byrne and Fiess, 2016), highlight the relevance of investigating bank ratings assigned by GRAs. This Chapter is focused on S&P ratings because prior research shows that S&P provides a more accessible dataset, is the most active GRA in rating actions, and has a greater tendency than other GRAs to take a lead in rating changes (Gande and Parsley, 2005; Ferreira and Gama, 2007; Adelino and Ferreira, 2016; Ballester and González-Urteaga, 2017; Drago and Gallo, 2017). Thus, a sample of 145 banks (4.284 observations) from 11 countries, with quarterly long-term issuer credit ratings based on the national and global scale assigned by S&P, during July 2006 to December 2015 is employed. Nevertheless, Moody's and Fitch are also included to test the effects of competition between GRAs as a driver of the ratings assigned by S&P.

To test the main hypothesis and sub-hypotheses, the Chapter selects a set of financial and accounting ratios from Bankscope, which are then matched with the available rating data. The selection of these variables follows the literature on bank rating determinants (Poon and Chan, 2008; Bissoondoyal-Bheenick and Treepongkaruna, 2011; Caporale et al., 2012; Shen et al., 2012; Hau et al., 2013; Massa and Žaldokas, 2014; Tennant and Sutherland, 2014; Ebeke and Lu, 2015). Besides the banks' internal performance, the Chapter also incorporates other factors that can influence NSR or GSR assignments. Namely, the bank's international connectivity (consistent with Di Pietra et al., 2014), and the type of ownership (consistent with Vazquez and Federico, 2015). The ratings of the other two GRAs are also incorporated to measure the effects of the competition among GRAs (following Becker and Milbourn, 2011) in S&P's initial rating assignments.

The results show that GSR assignments are more likely in larger size banks, with international business (consistent with Han et al., 2012), while NSRs have a higher probability of being assigned to smaller banks with domestic business. However, the sample employed in the Chapter shows that S&P often assigns both GSRs and NSRs at the same time, although GSR assignments at the same time as NSR assignments are less likely in larger banks compared to assignments of only NSRs. These results suggest a complementary relation between GSRs and NSRs. Regarding rating competition, this Chapter shows that ratings from the other two GRAs influence the decision of being rated by S&P in both types of ratings, although the influence of each GRA differs between NSR and GSR.

To the best of my knowledge, the current Chapter offers an original contribution to the sparse literature on NSRs. The novelty of this study is derived from the unique perspective on the credit rating literature, examining the drivers of assigning national or global ratings to banks by S&P. Also, the aim of the original research design is to determine a potential relationship between national and global ratings. The originality of the research questions and design is reinforced by the uniqueness of the dataset, constructed by combining information from Bankscope and Interactive Data Credit Ratings in Emerging Markets (henceforth, ID-CREM)[61], and by using complementary information from the three GRAs. Furthermore, previous research on NRAs and comparisons with GRAs have been mainly country-specific, while the current study widens the scope by analysing S&P's initial national and global ratings assigned to banks located in 11 emerging economies. In addition, by considering bank ratings assigned by Fitch and Moody's as potential drivers of bank ratings assigned by S&P, the study

[61] The rating data was made available from my supervisor's database.

sheds light on the effects of competition in the credit rating industry in emerging economies, a topic that is absent from prior literature.

The results of the study are insightful for different market participants such as regulators, CRAs, financial and non-financial institutions and portfolio managers because they present a new analytical perspective on GRAs' rating assignments in emerging economies. Moreover, as regulators have discussed the benefits of establishing a regional credit rating system in emerging economies (FPRI, 2013), this study can contribute to the debate by showing how relevant are NSR for banks in emerging economies. The findings underline the relevance of considering NSR from GRAs when analysing domestic ratings, challenging the market segmentation between GRAs and NRAs found in Asian markets by Ferri and Lacitignola (2010). Furthermore, the Chapter shows that NSR are more likely assigned in countries with high sovereign ratings compared to GSR. Thus, like GSR, NSR assignments by GRAs should also be considered in the investment decision-making process of international market participants, and by regulators as a control variable for international capital inflows to emerging markets.

The Chapter is organised as follows: Section 4.2 presents prior relevant literature and Section 4.3 presents the research questions and hypotheses. Section 4.4 describes the data sample and presents summary statistics, while Section 4.5 presents the empirical design used to test the hypotheses. Section 4.6 discusses the empirical results and robustness tests, and Section 4.7 concludes the Chapter.

4.2 Literature review

Academics describe the credit rating industry as an oligopoly, with GRAs leading the rating business (see Section 2.1). Combined, the three GRAs assign more than 94% of the ratings reported by the U.S. Securities and Exchange Commission (SEC, 2018) and by the European Securities Markets Authority (ESMA, 2018). As a result, the main focus of the literature on credit ratings is GRAs' rating practices (see Section 3.2), although more than 200 NRAs are operating worldwide (Marandola, 2016).

The scarce literature on NRAs shows that their presence contributes to improving the development of the financial sector in emerging markets (see Section 3.3.1). For instance, Ferri and Lacitignola (2010) find that the presence of NRAs has a positive effect on the development of the financial market in 49 countries (emerging and developed economies). They suggest that the contribution obeys to the segmentation in the credit rating industry, as GRAs rate larger, internationally oriented firms, while NRAs tend to rate small companies with less international connections. Thus, the type of companies rated by NRAs improves rating coverage, which has a positive effect on the development of the financial system. Likewise, Marandola (2015) finds that NRAs' presence is relevant in countries where the financial market is developing, showing an increase in the market capitalization and the outstanding bonds traded in international markets after the NRAs appeared. The positive effect of NRAs on the economic development is also highlighted by Tsunoda et al. (2013), as they propose to create a new rating methodology for Small and Medium Size Enterprises (SMEs) for NRAs operating in Bangladesh, to take advantage of the NRAs' infrastructure and domestic knowledge.

There is also little research on GRAs' practices in emerging economies, despite the GRAs' significant expansion in these countries in the last 10 years, directly (by acquiring an NRA or through a subsidiary) or indirectly (through partnerships and joint ventures). GRAs have stated that emerging economies have strategic importance, as they contribute to diversifying their revenues (see Moody's, 2018a; S&P Global, 2019). Hence, examining the drivers of rating assignments (GSR and NSR) in these economies has high relevance. Since GRAs are capable of assigning GSRs and NSRs, they are potential competitors for NRAs, however, this aspect has been only examined for China in the current academic literature (see Jiang and Packer, 2017; Livingston et al., 2018). The reputation value of GRAs' GSRs (see Han et al., 2012) could also be transferred to the NSRs, which would imply that GRAs' NSRs could benefit from a certification effect and should be therefore highly valuable for large issuers. Additionally, similar to NRAs, the presence of other GRAs can act as a measure of the demand for ratings and can contribute to strengthening the country's financial regulation. As these two aspects have high relevance for GRAs (see Marandola, 2016), the presence of competitors in these countries can increase the probability of GRAs' rating assignments.

The analysis of GRAs' ratings drivers are particularly relevant in the banking sector of emerging economies, as loans continue to be the prominent source of funding in these countries (see Nagano, 2018). This also means that assigning GSR to cross-listed banks can provide additional information on the robustness of the accounting standards applied in the country (see Bae et al., 2013). Moreover, because of the strong link between sovereign risk and bank risk (see Williams et al., 2013), GSR assignments can become a competitive measure of the sovereign risk against other CRAs when comparing banks in a cross-country setting (Ferri et al., 2001). Furthermore, GRAs' will avoid issuing GSRs to banks with NSR close to the investment grade rating threshold because the assigned GSR would probably be in a speculative category. Moreover, in countries with low sovereign risk, assigning NSR to banks would become informative if the bank has a high GSR due to the ceiling effect (see Williams et al., 2013). These aspects show the importance of examining the determinants of GRAs' rating assignments in emerging markets' banks.

Regarding the studies on CRAs with regional coverage, they are mainly focused on Japan and the US, where International Rating Agencies (Henceforth, IRAs) have a well-established rating business (see definitions of CRAs in Section 2.2). Research shows that, despite assigning higher ratings to Japanese bonds, Japanese IRAs' rating changes have less impact on the yield spreads than GRAs' rating changes, although both have informational value (Packer, 2000; Li et al., 2006; Han et al., 2012) (see Section 3.3.2). On the contrary, when comparing GRAs with Egan-Jones (EJ), an IRA[62] from the US working under a subscriber-pay business (see Section 2.4 for definitions), studies show that EJ's rating changes have more relevance in the market pricing and are timelier than the rating changes by GRAs. Previous research also finds evidence of leading behaviour by EJ compared to GRAs. Milidonis (2013) shows EJ's rating changes lead the rating changes by S&P and Fitch, while Bruno et al. (2016) find that EJ's ratings lead Moody's ratings, before and after EJ acquires the status of Nationally Recognized Statistical Rating Organization (NRSRO) (see Chapter 3, Section 3.3.3).

The credit rating literature shows that GSRs from GRAs (see Section 2.3 for definitions on ratings) are the main focus of research, even when comparing GRAs with IRAs. On the other

[62] Egan-Jones is classified as IRA because it rates at a regional level (rate securities issued by a foreign government) and at a national level.

hand, research on NSRs from GRAs is scarce, although it has been increasing in recent years as GRAs have been expanding their activity through affiliates and joint ventures (see Section 3.3.2). The limits on doing cross-country comparisons when using NSRs might explain the bias towards GSRs, although even in country-specific studies, GSRs are often preferred (e.g. Han et al., 2012; Jiang and Packer, 2017, 2019). Another possible factor influencing the limited research on NSRs could be the absence of a regional regulatory authority similar to ESMA in Europe (see Section 2.2), which constrains the availability of high quality information (FPRI, 2013).

The country-specific studies that use NSRs from GRAs are mainly focused on China and Korea (See Section 3.3.2). For instance, Poon and Chan (2008) examine the stock returns reaction to rating changes by Chinese NRAs, finding that the market reacts strongly when these Chinese NRAs take negative rating changes, as they usually assign more positive ratings than GRAs. Jiang and Packer (2017) examine the determinants of the rating differences between Chinese NRAs and GRAs[63] and find that larger size and higher leverage increases the probability of receiving higher ratings by Chinese NRAs, while higher profitability and state-ownership improve the likelihood of receiving better ratings by GRAs. Livingston et al. (2018) documents that Chinese NRAs and Chinese NRAs affiliated to GRAs have different rating scales, although both types of ratings are priced by investors. Jiang and Packer (2019) find similar results as Livingston et al. (2018) between Chinese NRAs and GRAs. Both have an impact on corporate bond yields despite having significant differences in the rating scales. Considering the rating quality, Hu et al. (2019) find more conservative behaviour in Chinese NRAs after China Bond Rating, an NRA under a mixed subscriber and public-utility paid business model, started operations (See Section 3.3.2).

For Korea, Ferri et al. (2013) investigate the effect on the Korean corporate bond prices of the rating changes of Korean NRAs with or without affiliation to GRAs. They find that rating changes from NRAs that are not affiliated to GRAs have a larger impact on the market because their local expertise is highly valued by investors. From a perspective of rating quality, Joe and Oh (2017) argue that an increase in the percentage of ownership of Korean NRAs by GRAs has deteriorated the quality of the ratings, following the same approach to competition as Becker and Milbourn (2011). Moreover, Park and Lee (2018) find evidence of rating shopping

[63] They include the global scale ratings by GRAs but perform a rating transformation to be able to compare them with the national ratings from NRAs (see Section 3.3.3).

and rating catering in the bond ratings assigned by the largest Korean NRAs: KIS, KR, and NICE.

The investigations of NSRs in countries outside Asia are especially scarce (see Section 3.3.3). For instance, in Israel, the information value of NRAs affiliated to GRAs is low (Afik et al., 2014). Bakalyar and Galil (2014) suggest the presence of rating shopping and differences in the rating scales between NRAs affiliated to GRAs. Chan et al. (2009) examine the role of a subscriber-paid NRA in Australia and find that their rating changes are more valuable for the market than ratings from GRAs, as they provide valuable private information for investors.

To summarize, investigations on NRAs, although scarce, show that they fulfil an important role in emerging economies. Firstly, by providing ratings for small companies with domestic business, NRAs improve the likelihood of accessing funding for these companies, promoting their growth. Secondly, NRAs extend the rating coverage and the assessment of the creditworthiness of the companies operating in the country, promoting financial system development. Since GRAs are capable of assigning NSRs and the significant influence they have on bond prices, not considering these ratings from GRAs' analysis could lead to biased conclusions.

4.3 Research question and hypothesis development

From the literature review, some studies suggest that GRAs and NRAs have a complementary rating business, where GRAs focus on rating large companies with international business and NRAs in rating small domestic companies. Fewer studies examine if there is a competitive advantage of GRAs over NRAs, as GRAs can assign both global and national ratings; if instead of a complementary business, GRAs' ratings can substitute NRAs' ratings. Livingston et al. (2018) show that investors demand lower bond yields in Chinese corporate bonds when ratings are assigned by GRAs' affiliates instead of Chinese NRAs. However, their study shows that the latter ratings are also considered by investors, suggesting that there is no perfect substitution between GRAs and NRAs.

The scarce research including NSRs from GRAs aims at finding their information value for investors, however, the drivers of NSRs assignments by GRAs have not been examined in the literature. The key aim of this Chapter is to analyse those determinants, focussing on banks from emerging economies. Thus, the main research question of the Chapter is: 'What are the drivers of banks' rating assignments by S&P in emerging economies?' Therefore, this question involves banks with NSRs or GSRs or both ratings. Furthermore, the analysis is focused only on ratings assigned by S&P. However, GSRs assigned by the other two GRAs are also included in the estimations as independent variables, testing the effect of competition on the ratings assigned by S&P (see Section 4.4.6.2).

The determinants of assigning an NSR can differ from the factors that drive assigning a GSR or assigning both types of ratings to banks. Moreover, an NSR assigned by S&P can influence a GSR assigned by S&P or vice versa. The aim of this Chapter is also to find how dynamic is the rating process[64] between those two types of ratings. To incorporate these aspects, a set of five research sub-questions are formulated:

a) *What factors influence whether S&P assigns global scale ratings simultaneously or after assigning national scale ratings to banks?*
b) *What factors influence whether banks have only national scale ratings assigned by S&P?*
c) *What factors influence whether banks have only global scale ratings assigned by S&P?*
d) *For global-rated banks[65], what are the determinants of having national scale ratings assigned by S&P?*

[64] Hereafter, the "rating process" refers to NSRs or GSRs assignments to banks by S&P.
[65] Banks with GSRs assigned by S&P before July 2006.

e) *For national-rated banks[66], what are the determinants of having global scale ratings assigned by S&P?*

Different factors can influence bank rating assignments by S&P. Firstly, S&P ratings can be driven by the bank's financial characteristics. Han et al. (2012) find that Japanese corporates with a weaker financial profile (high leverage, asset opacity, and high systemic risk), international connectedness and a higher number of bond issuances are more likely to perceive a certification effect from ratings assigned by GRAs. Hau et al. (2013) examine banks' characteristics and the quality of the assigned ratings and determine that larger banks with better financial performance tend to receive more positive ratings from GRAs. Jiang and Packer (2017) show that Chinese corporates receive positive ratings from GRAs when they are more profitable and state-owned and have low leverage. Nevertheless, Shen et al. (2012) document that the banks' financial performance is not a significant determinant of GRAs' ratings in emerging economies, because of high information asymmetries. These studies are considered in the selection of the variables and further description is presented in Section 4.4.2.

Secondly, banks' foreign exposure can drive S&P rating assignments. Bae et al. (2013) show that after being rated by S&P (at the global scale), corporations are more attractive for international investors as the rating "certifies" that their accounting practices are conservative. Bell et al. (2012) and Di Pietra et al. (2014) argue that firms located in countries with feeble institutional environment can improve their corporate governance outlook by offering their shares in the foreign market (cross-listing firms). They call this behaviour "the bonding hypothesis", which suggests that the business of cross-listed firms are more exposed to stringent regulation, improving the firms' reputation towards international investors. Likewise, foreign ownership diminishes the probability of default as it suggests better risk management practices and access to funding through the parent company (Arena, 2008). From the literature findings, banks with foreign ownership would be more likely to receive ratings from a GRA.

Thirdly, S&P rating assignments can be related to rating competition between GRAs. When companies are rated by a GRA, the introduction of a new rating by other GRA can exert upward pressure on the former rating (see Becker and Milbourn, 2011). Therefore, under conditions of competition between GRAs, a second rating assigned by other GRA would improve the bank's rating from the GRA that assigned the initial rating. A second possibility is that rating assignments are the indirect result of an acquisition process of an NRA by a GRA. For instance,

[66] Banks with NSRs assigned by S&P before July 2006.

when Duff & Phelps (D&P) was acquired by Fitch Ratings in Colombia, the process involved reviewing and adjusting D&P's rating methodology to comply with Fitch's standards. As a result, several companies previously rated by D&P before the acquisition had an adverse adjustment in their ratings. Although the adjustments were temporary and Fitch reversed them (Fitch Ratings Colombia S.A., 2009), Fitch faced a legal process from one of the affected credit institutions (Camara de Comercio de Bogota, 2012), which later cancelled the contract with Fitch. In the current Chapter, the effect of the competition is incorporated by including Fitch and/or Moody's bank ratings as independent variables.

S&P GSR assignments can also be the result of NSR assignments by S&P in an earlier period. In countries with high default risk, NSRs at the highest category of the scale (AAA or near) are not informative to foreign investors, as they do not reflect the sovereign risk. In these cases, it is more likely that S&P assigns GSRs replacing or additional to NSR assignments. In contrast, NSR assignments at the lowest investment category would probably result in the assignment of speculative GSRs, which would not provide added value to investors. Accordingly, S&P would be less likely to assign GSR in banks with "borderline national ratings" like BBB-\Baa3 and BB+\Ba1. The category of the NSRs is incorporated in the analysis in the robustness tests (see Section 4.6.1).

From the main research question and the potential determinants of S&P ratings discussed in this section, the main hypothesis proposed is the following:

- ***Hypothesis 1 (H1):*** *Rating assignments by S&P (national, global ratings or both ratings) are influenced by banks' characteristics and the competitive setting.*

H1 examines whether S&P is selective when it assigns ratings and thereby prefers to rate banks with better financial performance because of reputational concerns (see Section 3.2.1). This question is addressed by selecting financial variables as potential determinants of the NSR and GSR assigned by S&P. Moreover, *H1* tests whether any competition with Moody's or Fitch assigned by NSR or GSR influences S&P rating assignments. Thus, *H1* links S&P rating assignments with rating catering, involving aspects such as market share, reputation and revenue concerns (see Section 3.2.2).

To differentiate between the drivers of NSRs from the drivers of GSRs, and also acknowledge the dynamic between NSRs and GSRs mentioned in the research sub-questions, five sub-hypotheses are developed as follows:

- ***Hypothesis 1a (H1a):*** *S&P is more likely to assign global ratings to banks with a larger size, with good financial performance, international connections and previously (or simultaneously) rated by S&P at the national level or by another GRA.*

- ***Hypothesis 1b (H1b):*** *S&P is more likely to assign national ratings to banks of smaller size, with domestic ownership and good financial performance.*

Ferri and Lacitignola (2010) highlight that, in emerging economies, banks with larger size and stronger international connections are rated by GRAs while smaller banks owned by locals are rated by NRAs. *H1a* and *H1b* challenge the findings of Ferri and Lacitignola (2010) by examining the effect of size and type of ownership in GRAs' GSR *(H1a)* and NSRs *(H1b).* Thus, these hypotheses relate to the literature on market segmentation. Furthermore, *H1a* is particularly related to the literature on GRAs' certification effect (see Section 3.2.1), as it examines the effect of GRAs' reputation on NSR in emerging economies (see Section 3.3.1).

- ***Hypothesis 1c (H1c):*** *S&P is more likely to assign global ratings to banks of larger size, previously rated by other GRA and cross-listed.*

H1c relates to the aspect of the value of reputation concerns (see Bolton et al., 2012). Thus, *H1c* investigates the relation of GRAs' GSR assignments with the financial performance and corporate governance quality of the sampled banks. It also highlights if competition among GRAs, discussed in Section 3.2.2 in emerging economies, influences S&P GSR assignments.

- ***Hypothesis 1d (H1d):*** *Banks with global ratings assigned by S&P, with good financial profile and local ownership would have additional national ratings assigned by S&P.*

H1d highlights the dynamics of GSR and NSR rating assignments by S&P. It is related to the literature that discusses the role of NSR in emerging economies (see Section 3.3.2). The main objective of *H1d* is to investigate whether NSR incorporate the reputational value (or certification effect) of GSR for emerging market banks, an aspect that has only been previously examined in China by Livingston et al. (2018).

- ***Hypothesis 1e (H1e):*** *Large banks with national ratings assigned by S&P, located in countries that have experienced sovereign rating downgrades, would have additionally global ratings assigned by S&P.*

H1e also examines the dynamics of GSR and NSR rating assignments by S&P from a different perspective because it examines the influence of NSR on GSR assignments considering the level of sovereign risk. It is related to the literature that highlights the important role of GRAs' sovereign ratings in emerging economies (see Section 3.3.1) and the strong connection between sovereign risk and GRAs' GSR assigned to banks in emerging economies (see Williams et al., 2013).

4.4 Dataset

This Section presents the description of the rating data and financial and accounting variables used to examine the determinants of NSRs and GSRs assigned by S&P. Sections 4.4.1 describes the rating dataset. Sections 4.4.2 present the definition of the financial and accounting variables used in the estimations. Section 4.4.3 details the summary statistics of the financial data before the matching process with the rating data. Section 4.4.4 details the sample after matching the credit rating dataset with the financial and accounting information. Section 4.4.5 describes other explanatory variables included in the estimations. Finally, Section 4.4.6 presents the summary statistics of the sample after matching the rating data with the financial and accounting variables.

4.4.1 Bank credit ratings

The dataset consists of quarterly long-term issuer credit ratings based on the national and global scale assigned by S&P, during July 2006 to December 2015 (hereafter, the period of analysis)[67], for 11 countries: Argentina, Brazil, China, Colombia, Indonesia, Kazakhstan, Mexico, Nigeria, Russia, South Africa and Thailand. The criteria for selecting the sampled countries is based on the financial data availability in Bankscope database. The main source of the rating data is Interactive Data Credit Ratings in Emerging Markets (ID-CREM).[68] Hence, following Alsakka and ap Gwilym (2010), S&P ratings are transformed into numbers based on a 20-point numerical scale: Aaa/AAA = 20, Aa1/AA+ = 19, BBB-/Baa3 =11,.., CCC+/Caa1 = 4, CCC-/Caa3 = 2, CC = 1, SD = 1, D/Ca = 1, RD/C = 1. For the matching process with the financial data, the ID-CREM rating sample is divided into NSRs and GSRs (based on the 20-point numerical scale for each type of rating). Information on the available quarters in the ID-CREM database is shown in Table 4.1.[69]

Table A 4.1 in the Appendix presents the list of the sampled banks, including the name, country, and dates of the initial NSR or GSR assigned by S&P. Table A 4.2 in the Appendix presents the number of banks with initial NSR or GSR(or both) assigned by S&P, from the matched sample (145 banks), per country. The most common case corresponds to banks with GSRs and NSRs assigned by S&P on the same day (52 banks). A total of 41 banks have ratings assigned

[67] The period of analysis is selected according to the data available on S&P's NSRs from the Interactive Data Credit Ratings in Emerging Markets database.
[68] The rating data is available from my supervisor's database for the entire sample period.
[69] Credit watch and outlook announcements that could accompany each rating category are not accounted for in this study because the analysis is focused on the initial ratings assigned by S&P.

by S&P before the period of analysis. 32 banks receive NSRs and have GSRs assigned in a previous period (GS-rated banks), and 5 banks receive GSR and have prior NSRs assigned by S&P (NS-rated banks). S&P assignments of only GSRs (NSRs) occurs in 5 (10) banks during the period of analysis. Russia, Brazil and Kazakhstan have the highest number of banks with NSRs and GSRs assigned by S&P on the same day, while the highest proportion of banks with NSR assignments is from Mexico.

4.4.2 Description of bank-level variables

The CAMELS[70] method is used by academics and other market participants to predict the risk exposure of a financial institution based on the analysis of variables that cover the assets, liabilities and equity performance: capital adequacy, asset quality, management, earnings, liquidity and sensitivity to market risk. For instance, Bassett et al. (2015) examine the supervisory stringency to rate banks and find that the effect of supervision standards haven't changed drastically since the 1990s. To test their hypothesis, they use the CAMELS rating methodology to decide which explanatory variables should be used in their empirical model. For this Chapter, the selection of variables follows the CAMELS methodology and the literature on bank rating determinants (Bissoondoyal-Bheenick and Treepongkaruna, 2011; Caporale et al., 2012; Shen et al., 2012; Hau et al., 2013; Tennant and Sutherland, 2014; Ebeke and Lu, 2015).

The variables selected are retrieved from Bankscope and are collected at a quarterly frequency for the period of analysis. The information is collected under Bankscope's fiscal mode; therefore, the information of each quarter is based on the company fiscal year end-date. Moreover, to avoid the survivor bias (see Lemmon et al., 2008), the sample incorporates active and inactive[71] banks from the selected sample of countries, during the period of analysis. The definition of the selected financial and accounting variables (see Table 4.3) and the literature supporting the choice is as follows:

$Size$ corresponds to the natural log of total assets, and it is a variable commonly used in bank's literature, with the strongest effect in credit ratings (e.g. Jiménez et al., 2010; Shen et al., 2012; Bae et al., 2013; Hau et al., 2013). The variable *total assets* is measured in thousands of USD

[70] The word CAMELS comes from the initial letter of each aspect covered in the methodology.
[71] Following the definition set by Bankscope, for the current Chapter the term "inactive bank" refers to one of the following options: banks which go bankrupt, are dissolved (absorbed, merged or demerged), in liquidation or are inactive for unknown reasons.

and has been converted using the exchange rate prevailing at the date of each report (closing date of the statement).[72]

$Capital$ has three definitions: i) *Capitalratio*, which according to Bankscope is "the total capital adequacy ratio under the Basel rules. It measures Tier 1 + Tier 2 capital, which includes subordinated debt, hybrid capital, loan loss reserves and the valuation reserves as a percentage of risk weighted assets and off-balance sheet risks"; ii) *Tier 1* which is defined by Bankscope as: "the shareholder funds plus perpetual non-cumulative preference shares as a percentage of risk weighted assets and off-balance sheet risks measured under the Basle rules", and iii) *Leverage* which is the ratio of equity to total assets, and measures the percentage of the company's assets who is owned by the shareholders (equity capital) and does not come from usage of debt. Capital is a common financial ratio found in bank risk literature (Leung et al., 2015; Anginer et al., 2018) and is usually included in the determinants of bank ratings (Bissoondoyal-Bheenick and Treepongkaruna, 2011; Shen et al., 2012; Salvador et al., 2014; Huang and Shen, 2015).

$Asset\ Quality$ ($NPLratio$) is a variable that incorporates the effect of the banks' credit risk. Loans represent a high proportion of the banks' assets. Thus, *Asset quality* is measured by the *ratio of non-performing loans: impaired loans (NPLs) to gross loans*. Numerous studies use the loan portfolio quality as a determinant of global bank ratings assigned by GRAs (Bissoondoyal-Bheenick and Treepongkaruna, 2011; Shen et al., 2012; Salvador et al., 2014, 2018).

$Profitability$ is a variable that proxies the financial performance of the bank and has two definitions: i) *ROAA*, which is the return on average assets, and is an indicator of the ability of the bank to manage their assets and make profits; ii) *Net interest* which represents the ratio of net interest income to average earning assets, and indicates how well the bank manages their investments compared to their obligations. Salvador et al. (2014, 2018) find that profitability is a significant determinant of the bank's global ratings.

Trading which is the ratio of non-interest income to gross revenues, and represents how much of the bank's income is generated from secondary activities linked to their main lending business, like transaction fees, fees for inactive accounts, management fees, etc. Morgan (2002)

[72] Bankscope indicates that the exchange rates are sourced from the International Monetary Fund (IMF) website and refer to the closing date of the statement. The exchange rates from the IMF are updated monthly and correspond to the rate valid at the closing date of the month.

argue that GRAs perceive banks with a high level of trading fees more opaque, while Hau et al. (2013) notes that bank trading revenue is underestimated by GRAs' ratings.

$Efficiency$ is defined as *total operating expenses by total operating income* and it is collected from Bankscope. Tennant and Sutherland (2014) argue that efficient banks can earn profit from fee activities. Shen et al. (2012) note that ratings improve when the cost to income ratio decreases, although when they divide the sample between high income and emerging economies, in the latter, the efficiency is no longer a significant determinant of the ratings.

$CostDebt$ is the *ratio of interest expenses to average interest-bearing liabilities* and is defined by Bankscope as "*the average rate of interest the bank is paying on its deposits and other interest-bearing liabilities*". Previous studies show that international activity is associated with better global ratings and lower cost of funding through debt (Reeb et al., 2001; Han et al., 2012). Specifically, Banks with larger size and systemically important face fewer interest costs because the market discipline is less effective (Bertay et al., 2013). Accordingly, large banks would be more prone to global ratings than smaller banks.

$Liquidity$ is focused on the asset/liability management of the bank, and it can be measured by: i) *NetLoanTA*, that is the ratio of net loans to total assets and indicates what is the size of their loan portfolio compared to the assets. A higher ratio would imply that the bank has a large loan portfolio and less liquidity.; ii) *NetLoanD* is the ratio of net loans to deposits and short-term funding and shows the availability of liquid funds to cover the demands from their loan business; and iii) *LiqAssets* corresponds to the ratio liquid assets to deposits and short-term funding and it is a proxy of the obligations that the bank would be able to meet if they were unexpectedly withdrawn. Previous studies find that higher loans increase the perception of uncertainty by GRAs, as it is a proxy of credit risk (Morgan, 2002; Iannotta, 2006). Moreover, liquidity has been used in the rating literature as a determinant of bank ratings (Poon et al., 2009; Shen et al., 2012; Salvador et al., 2014; Huang and Shen, 2015) and as a determinant of global bank lending (Aysun and Hepp, 2016).

The proxies of the variables *Capital*, *Profitability and Liquidity* selected for the estimations are: *Capitalratio*, *Netinterest* and *NetLoanTA*, respectively. The selection of these variables is based on the empirical findings of the bank risk and bank rating literature (see Table A 4.3 in the Appendix) and on the availability of information in Bankscope.[73] Nevertheless, the other

[73] Bankscope has gaps in the data and the information of the variables is not uniformly distributed across the period of analysis.

alternative measures of the variables *Capital, Profitability* and *Liquidity* are used in the robustness checks (see Section 4.6.2).

4.4.3 Trimming bank-level characteristics before matching with ratings

The financial ratios of some banks include observations defined as "n.s.", which according to Bankscope are: "any of the financial ratios having a value above 1000% could hardly be considered as significant to the analyst. Consequently, any ratio with a value above 999.99 % is noted "ns" ("Not significant")". To prepare the summary statistics for the quarterly observations of the bank financial variables over the period 2005 to 2016, the dataset is adjusted and all observations with "n.s." values are eliminated from the sample. To reduce the possible impact of outliers in the dataset, two methods are considered: winsorize the data at the 99.5 percentile and below the 0.5 percentile of the distribution or trim the data, which ignores extreme values (above the 99.5 percentile and below the 0.5 percentile of the distribution). Trimming is preferred to winsorizing as is a common approach in the bank literature to account for data errors and eliminate outliers (Lemmon et al., 2008; Lemmon and Roberts, 2010; Jones et al., 2013).

After trimming the data, 17 banks exit the sample (9 from Brazil, 3 from Mexico, one from Kazakhstan, one from Argentina, one from Indonesia, one from Russia and one from Thailand) and 50 observations are deleted from each of these variables: total assets, leverage, ROAA, tier1, capital ratio, NetLoanTA, NetLoanD, LiqAssets, NPL ratio, profits, efficiency, and trading. Table A 4.4 in the Appendix presents the correlation matrix of the trimmed financial variables, estimated to find the dependence between the financial variables and any possible collinearity. As expected, there is evidence of a strong correlation between the proxies of *Capital*: *Leverage, Tier 1* and *Capitalratio*, supporting possible multi-collinearity. However, as mentioned in Section 4.4.2, only *Capitalratio* is included in the estimations and the other two variables are included independently in the robustness tests.

4.4.4 Matching bank credit ratings with the financial and accounting information

Table 4.2 presents the summary of the final sample. 1672 banks had information available in Bankscope (initial sample). However, after trimming the financial data, only 420 banks (4.284 observations) meet the criteria of complete financial and accounting data for the period of analysis in Bankscope (henceforth, trimmed sample). Subsequently, the trimmed sample is matched with the quarter observations with NSR and/or GSR from the database ID-CREM (henceforth, matched sample). The matched sample is an unbalanced panel data of 145 banks from 10 countries, as Argentinean banks are excluded because their financial and accountant information does not match any ratings in ID-CREM. However, Argentinean banks are part of the "Unrated sample", which corresponds to the remaining 275 banks from the trimmed sample of 420 banks.

Table A 4.5 in the Appendix presents a description of the matched sample considering the number of observations with NSRs and/or GSRs. Panel A shows the year-observations per region and Panel B presents the year-observations per country. The Latin American countries of the sample have the highest number of bank-quarter NSRs and GSRs (735), while Africa holds the lowest number of NSRs and GSRs. Considering the observations per country (Panel B), Brazil has the highest number of GSR assignments (354) and Mexico that has the highest number of observations with NSR assignments (387). In contrast, Colombia has the lowest number of observations with GSRs and does not have any observation with NSRs. Moreover, except for Mexico, the number of observations with GSRs exceeds the observations with NSRs. There is an upward trend in NSRs and GSRs observations, which could be explained by the availability of financial information in emerging economies, which increases after 2010. Thus, the probability of having financial information matched with rating data increases after 2010.

Table A 4.6 in the Appendix presents the correlation matrix of the NSR and GSR observations per country during the analysed period. The Table reveals a high correlation between NSR and GSR in Brazil, Kazakhstan, Mexico, Nigeria, Russia, and South Africa. The result could be explained by the high number of NSR and GSR assigned to banks by S&P in the same quarter, and it is evidence of how relevant it is to consider NSR assigned by S&P when analysing the GRA.

4.4.5 Other explanatory variables

Besides the financial variables, the estimation also includes the bank's international exposure and the competition with other GRAs as possible drivers of the rating assigned by S&P (see description of variables and summary statistics in Tables 4.3 and 4.4, respectively). As a proxy of the international exposure of the banks, two variables are included: *Bonding* and *Ownership*. The definition of *Bonding* follows Di Pietra et al. (2014), who find that firms located in countries with weak institutional environment will enhance their corporate governance system by registering in an international stock exchange. *Bonding* is a dummy variable that takes the value of one from the moment the bank is listed in one or more foreign stock exchange (cross-listed), or zero if it is just listed in the local stock exchange or unlisted. The information is collected from Bankscope (defined in Bankscope as: “stock exchange(s) listed”) and complemented with Capital IQ, Bloomberg, and information from international stock exchanges and stock quota websites.[74] From the information collected, 31 banks from 7 countries are cross-listed and 112 banks are only listed in the domestic stock exchange or not listed.

The variable *Ownership* is defined as a dummy variable that takes the value of one if the country of origin of the global ultimate owner (GUO) is different from the country where the bank is located. The country of origin of the GUO of each financial institution is collected from Bankscope.[75] According to the literature, the bank’s ownership structure has a significant influence on the bank’s resilience when the economy is exposed to adverse scenarios like the global financial crisis (e.g. Vazquez and Federico, 2015). From the matched sample, 107 banks have domestic GUO and 38 banks have foreign GUO.

The effect of competition from other GRAs is based on the credit rating literature and has three arguments. Firstly, Becker and Milbourn (2011) argue that the presence of a third GRA (Fitch) exerts upward pressure on the ratings assigned by the other two GRAs, as they are less concerned about the reputation and more aware of the competition. Likewise, Griffin et al. (2013) show that GRAs adjust their rating standards to match the competitor, as they are more focused on their income or their market share. Secondly, Marandola (2016) argues that the rating industry in emerging economies is still growing and the demand for ratings is limited because the financial markets are still developing. Thus, the presence of GRAs usually follows NRAs because NRAs’ presence convey information on higher development of the financial system, stronger bank supervision and demand for ratings. This Chapter contends that additionally to NRAs’ signals, bank ratings assigned by Moody’s and/or Fitch can also convey information on the level of development of the financial system, better institutional environment and demand for S&P’s ratings. A third argument of the influence of competition between GRAs, is that the size of the capital markets is smaller in emerging than in developed economies, as funding through the capital market is constrained due to high information asymmetries (Avendaño and Nieto-Parra, 2015; Nagano, 2018). Hence, it is highly likely that

[74] http://www.quotenet.com; http://cbonds.com.

[75] In the project proposal, the share of foreign investors’ holding of domestic corporate bonds as percentage of total outstanding amount of local currency bonds was suggested as a measure of the bank’s international exposure, following the literature on the topic (Ebeke and Lu, 2015; Massa and Žaldokas, 2014). However, the available databases do not include the mentioned ratio.

S&P assigns ratings to the same institutions rated by other GRA (or GRAs) if S&P wants to increase its market share or earn higher income. Based on these three arguments, this Chapter proposes that under conditions of competition between GRAs, bank rating assignments by Fitch or Moody's (or both) would improve the likelihood of S&P rating assignments.

To test the influence of competition on the ratings assigned by S&P, this Chapter incorporates in the model two dummy variables that takes the value of one if the bank has a rating based on the global (or national) scale by Fitch (dummy called *Fitch*) or Moody's (dummy called *Moody's*), assigned by these GRAs in the prior year to the initial rating assignment by S&P. If S&P assigns the rating before the third quarter of 2006 (Henceforth, 2006q3), and the bank has also a rating from Fitch or Moody's or both assigned before 2006q3, the dummy variable takes the value of one in the period of analysis, unless the ratings by Fitch or Moody's are withdrawn. The dates of the long-term foreign currency ratings assigned by Fitch and Moody's are sourced from Capital IQ, and websites of Moody's and Fitch Ratings. From the matched sample, Fitch and/or to Moody's assigned ratings to 83 banks of the matched sample of 145 banks.

To control for the economic, political and financial situation of the sampled countries at the time of the rating assigned by S&P, the model incorporates the variable *Sovrating*, which is the average of the quarterly numerical sovereign ratings assigned by S&P, Moody's and Fitch. The date of sovereign ratings by S&P is available from ID-CREM from 2006 to 2015, and any missing data is sourced from Capital IQ (for S&P). The sovereign ratings assigned by Fitch and Moody's are collected from their websites. Following Alsakka and ap Gwilym (2010b), the sovereign ratings of S&P, Fitch and Moody's are transformed according to the 20-point numerical scale.

Additionally, a popular measure of financial uncertainty in the credit rating literature is the CBOE Volatility Index (VIX), which measures the volatility implied by options contracts on the S&P 500 index (Hartelius et al., 2008; Böninghausen and Zabel, 2015; Vu et al., 2015). In the current Chapter, the variable is included to control for the investor's sentiment towards risk.

4.4.6 Summary statistics after the matching with the rating data

Table 4.3 presents the definition and source of the financial and non-financial variables used in the estimations. The summary statistics from the trimmed sample (420 banks, 4.284 observations) are shown in Table 4.4. The average *Size* of the banks from the sample is US$67,188 million (Table 4.4 reports the natural logarithm of the book value of total assets).

The trimmed sample includes banks rated and not rated by S&P. Banks rated by S&P have an average size of US$114,288 million, while banks not rated by S&P have an average size of US$26,062 million (unreported by Table 4.4). This is preliminary evidence that larger banks tend to be rated by S&P.

The mean of the variable *ROAA* is 1.35%, which indicates a high level of profits compared to the average level in the European and US banking sector.[76] The minimum *ROAA* -9.97% and corresponds to the African Bank Limited, a small bank from South Africa with US$6.002 million of assets, not rated by S&P. Another variable to highlight is *Capital Ratio* that has a mean of 17.35% which shows a healthy banking sector. However, the minimum value of *Capital Ratio* of 7.56% is slightly below the regulatory minimum of 8% required by the Basel Committee and corresponds to SME Development Bank of Thailand, not rated by S&P. According to Moody's, which assigned a rating of Baa2 to SME Development Bank, capital adequacy is their main weakness and explains two capital injections received from the government in December 2015 and in September 2016 (Moody's, 2017).

The largest standard deviation corresponds to the variable *NetLoanD*, explained by a ratio higher than 200% for 17 banks rated by S&P, and 31 banks not rated by S&P. This ratio shows how significant is the mismatch between loans and deposits for these banks and it is only used in the robustness tests. The variable *LiqAssets* has the second highest standard deviation, explained by a ratio higher than 200% registered in four banks from Mexico and Brazil. Three of those four banks reported high levels of liquidity in 2007 and 2009 and one bank, American Express (Mexico) shows a higher ratio of *LiqAssets* since 2014. Further research shows that American Express (Mexico) has a national scale rating of mxAAA by S&P, which is supported, among other aspects, in their adequate liquidity to cover their operations (S&P, 2017). 61 banks reported negative ratios of *Trading*, which could be showing the high sensitivity of those banks to changes in the interest rates and the lack of profitability of activities different from the main loan business. The minimum value of the variable *Costdebt* is -13.6% while the maximum is 231.58%, however, the median is 5.35% and the standard deviation is 5.66%, which shows a stable distribution in the sample. The minimum and maximum value of the *Costdebt* corresponds to Rabobank in Brazil during 2008 and 2009, and the bank is rated only by Fitch.

[76] As a comparison, the average ROA of US banks from July 2006 to December 2015 was 0.83%, according to the Federal Financial Institutions Examination Council (2016). Moreover, the EBA (2015)(EBA, 2015) reports an average return on assets of 0.29% in the fourth quarter of 2015 and 0.20% in the fourth quarter of 2014.

The mean of the dummy variables *Bonding*, *Fitch and Moody's* are close to zero, which means that the sample has mainly domestic banks, primarily rated by S&P. The control variable *Sovrating* has an average numeric rating of 11.94, which is equivalent to a sovereign rating of BBB/Baa2 and has a low standard deviation. The lowest average sovereign rating corresponds to Argentina (4 or CCC+), Indonesia and Nigeria are rated at the speculative categories (9.1 or BB and 8 or BB-, respectively), and the highest average sovereign rating (17 or A+/A1) corresponds to China.

Panels A to F of Table 4.5 report the pairwise correlation matrix for the 14 (or 15 in the case of Eq. 4.6) explanatory variables that were potentially considered in Eq. (4.1) to Eq. (4.6). The results of the correlation matrices show no evidence of multi-collinearity.

4.5 Methodology

This Section presents and discusses the methods of investigating the drivers of S&P NSR and GSR assignments. Section 4.5.1 presents the six models designed to test the main hypothesis and the sub-hypothesis (see Section 4.3 and Table 4.6 for the details on the hypotheses), and Section 4.5.2 presents the expected sign and provides the rationale for those signs.

4.5.1 Binary probit model

To examine the drivers of having a rating assigned by S&P for banks in emerging economies (*Hypothesis H1 and sub hypotheses)* a binary probit modelling approach is employed. A binary probit[77] is a common approach used in the credit rating literature when the dependent variable is a binary or dichotomous variable (e.g. Iannotta, 2006; Han et al., 2009, 2013; Gonis et al., 2012; Jiang and Packer, 2019). In this Chapter, the binary probit approach is used to model the drivers of a bank's propensity to be rated by S&P. For *Hypothesis H1*, the model specification is as follows:

$$SPrating^{*}_{i,j,t} = \beta_i X_{i,j,t-4} + \gamma_1 Bonding_{i,j,t} + \gamma_2 Ownership_{i,j,t} + \gamma_3 Fitch_{i,j,t} + \gamma_4 Moodys_{i,j,t} + \gamma_5 Sovrating_{j,t} + \gamma_6 VIX_t + \delta YD + \phi CD + \varepsilon_{i,j,t} \quad (4.1)$$

Following Greene (2012), *SPrating** is an unobserved latent variable that is linked to the observed response variable *SPrating* by the measurement model:

$$SPrating_{i,j,t} = 1 \; if \; SPrating^{*}_{i,j,t} > 0$$

$$SPrating_{i,j,t} = 0 \; if \; SPrating^{*}_{i,j,t} \leq 0$$

The subscripts i, j, t denote bank, country and time (quarters), respectively. The binary variable *SPrating* takes the value of one from the quarter S&P assigns a rating (NSR or GSR or both), onwards, and zero if the bank is not rated by S&P. $X_{i,j,t-4}$ is a set of eight bank characteristics lagged four quarters (*t-4).* The lag follows prior literature, as current values of the variables could reflect additional information that was unknown when the rating was assigned (Salvador et al., 2014). $Bonding_{i,j,t}$ is the proxy of the bank's cross-listing; $Ownership_{i,j,t}$ is a dummy that takes the value of one if the bank has foreign ownership and zero if the bank has domestic

[77] A binary probit is a limited dependent variable model (LDV). An LDV can be binary or multinomial. In the case of binary models, the dependent variable reflects categorical choices; in the multinomial model, the dependent variable represents more than two outcomes, and have more specifications, which are levelled according to the choice. These choices can be ordered or not (see Greene, 2012)

ownership; $Fitch_{i,j,t}$ and $Moodys_{i,j,t}$ are included to capture the effect of competition between GRAs. The control variable $Sovrating_{j,t}$ is the quarterly average sovereign rating of S&P, Moody's and Fitch, and VIX_t is the volatility index. Full details of the explanatory variables are presented in Sections 4.4.2 and 4.4.5, and in Table 4.3. The model also incorporates a full set of year (YD) and country (CD) dummy variables, which is a common approach in the literature to control for possible unobserved macroeconomic and financial conditions, differences in development between countries in the sample, and endogeneity concerns about omitted variables (Lemmon and Roberts, 2010; Thompson, 2011; Jiménez et al., 2012).

The *research sub-question 1(a)* examines the drivers of S&P GSR assigned simultaneously or after assigning NSR. To test *Hypothesis 1(a)*, a binary probit model approach is employed (see Table 4.6 for further details) as follows:

$$GSRandNSR^*_{i,j,t} = \beta_i X_{i,j,t-4} + \gamma_1 Bonding_{i,j,t} + \gamma_2 Ownership_{i,j,t} + \gamma_3 Fitch_{i,j,t} + \gamma_4 Moodys_{i,j,t} + \gamma_5 Sovrating_{j,t} + \gamma_6 VIX_t + \delta YD + \phi CD + \varepsilon_{i,j,t} \quad (4.2)$$

*GSRandNSR** is an unobserved latent variable that is linked to the observed response variable *GSRandNSR* by the measurement model:

$$GSRandNSR_{i,j,t} = 1 \; if \; GSRandNSR^*_{i,j,t} > 0$$

$$GSRandNSR_{i,j,t} = 0 \; if \; GSRandNSR^*_{i,j,t} \leq 0$$

The binary variable *GSRandNSR* takes the value of one from the quarter S&P assigns a GSR and an NSR simultaneously or assigns a GSR to a bank with prior NSR,[78] onwards, and zero if it is an NSR-only bank.[79] The independent variables included in Eqs. (4.2) to (4.6) have the same definition as in Eq. (4.1).

The *research sub-question 1(b)* examines the drivers of NSR-only assignments by S&P. To test *Hypothesis 1(b)*, a binary probit model approach is used as follows:

$$OnlyNSR^*_{i,j,t} = \beta_i X_{i,j,t-4} + \gamma_1 Ownership_{i,j,t} + \gamma_2 Sovrating_{j,t} + \gamma_3 VIX_t + \delta YD + \phi CD + \varepsilon_{i,j,t} \quad (4.3)$$

*OnlyNSR** is an unobserved latent variable that is linked to the observed response variable *OnlyNSR* by the measurement model:

$$OnlyNSR_{i,j,t} = 1 \; if \; OnlyNSR^*_{i,j,t} > 0$$

[78] NSR assigned by S&P before 2006q3.
[79] When S&P assigns only an NSR, it is addressed as 'NSR-only' in Chapter 4.

$$OnlyNSR_{i,j,t} = 0 \; if \; OnlyNSR^*_{i,j,t} \leq 0$$

The binary variable *OnlyNSR* takes the value of one from the quarter S&P assigns an NSR, onwards, and zero if the bank is not rated by S&P. Considering the number of unrated banks (275) against banks that have an NSR after 2006Q3 (10), and to improve the reliability of the inference in the model, the variable *OnlyNSR* also includes banks from the matched sample which have an NSR assigned by S&P before 2006Q3 (See Table 4.6 for further details).

The *research sub-question 1(c)* investigates the drivers of GSR-only assignments by S&P. Accordingly, a binary probit model is used to test *Hypothesis 1(c)* as follows:

$$OnlyGSR^*_{i,j,t} = \beta_i X_{i,j,t-4} + \gamma_1 Fitch_{i,j,t} + \gamma_2 Moodys_{i,j,t} + \gamma_3 Sovrating_{j,t} + \gamma_4 VIX_t + \delta YD + \phi CD + \varepsilon_{i,j,t} \tag{4.4}$$

*OnlyGSR** is an unobserved latent variable that is linked to the observed response variable *OnlyGSR* by the measurement model:

$$OnlyGSR_{i,j,t} = 1 \; if \; OnlyGSR^*_{i,j,t} > 0$$

$$OnlyGSR_{i,j,t} = 0 \; if \; OnlyGSR^*_{i,j,t} \leq 0$$

The binary variable *OnlyGSR* takes the value of one from the quarter S&P assigns a GSR to non-rated banks, onwards, and zero if the bank is not rated by S&P. As the number of unrated banks is 275 and banks that have a GSR assigned after 2006q3 are only five, and to improve the reliability of the inference in the model, the estimation of the variable *OnlyGSR* also includes banks from the matched sample that have a GSR assigned before 2006q3 (see details in Table 4.6).

The *research sub-question 1(d)* examines the factors that influence whether a GS-rated bank[80] is assigned an NSR by S&P. The trimmed sample has 32 GS-rated banks that are assigned NSRs subsequently. The specification of the binary model to test *Hypothesis 1(d)* is as follows:

$$NSRating^*_{i,j,t} = \beta_i X_{i,j,t-4} + \gamma_1 Ownership_{i,j,t} + \gamma_2 Bonding_{i,j,t} + \gamma_3 Fitch_{i,j,t} + \gamma_4 Moodys_{i,j,t} + \gamma_5 Sovrating_{j,t} + \gamma_6 VIX_t + \delta YD + \varepsilon_{i,j,t} \tag{4.5}$$

*NSRating** is an unobserved latent variable that is linked to the observed response variable *NSRating* by the measurement model:

$$NSRrating_{i,j,t} = 1 \; if \; NSRating^*_{i,j,t} > 0$$

[80] GS-rated bank refers to NSR assignments to banks with prior GSR assigned by S&P.

$NSRating_{i,j,t} = 0 \; if \; NSRating^{*}_{i,j,t} \leq 0$

The binary variable *NSRating* takes the value of one from the quarter S&P assigns an NSR to a GS-rated bank, onwards, and zero if it is a GSR-only bank. Because of the small sample size, the estimation only includes year fixed effects.

The *research sub-question 1(e)* analyses the drivers of GSR assignments to NS-rated banks.[81] A binary probit model is used to test *Hypothesis 1(e)*, as follows:

$$GSRating^{*}_{i,j,t} = \beta_i X_{i,j,t-4} + \gamma_1 Sovrating_{j,t} + \gamma_2 VIX_t + \delta YD + \varepsilon_{i,j,t} \tag{4.6}$$

*GSRating** is an unobserved latent variable that is linked to the observed response variable *GSRating* by the measurement model:

$GSRating_{i,j,t} = 1 \; if \; GSRating^{*}_{i,j,t} > 0$

$GSRating_{i,j,t} = 0 \; if \; GSRating^{*}_{i,j,t} \leq 0$

The binary variable *GSRating* takes the value of one from the quarter S&P assigns a GSR to an NS-rated bank, onwards, and zero if it is an NSR-only bank. There are only five NS-rated banks with GSR assignments during the period of analysis. From those banks, only two are cross-listed and all of them are domestically owned, while only one NS-rated bank is cross-listed. Hence, the dummy variables *Ownership* and *Bonding* are dropped from Eq. (4.6), as they do not show variation in the estimation. Also, the GSR assignments to NS-rated banks and the NSR-only banks are located in Mexico or Brazil. Therefore, country dummies are omitted and Eq. (4.6) only includes year dummies.

To minimize potential endogeneity concerns related to omitted variables and partial out country-specific time-invariant unobserved effects and control for time shocks that might affect the banks in the sample, the estimations of Eq. (4.1) to (4.4) include a set of year and country fixed effects, while Eq. (4.5) and (4.6) only include year fixed effects. Nonetheless, there might be variables that are omitted that could be interesting for the particular examination of S&P rating assignments. For instance, since the level of corruption in emerging economies is highlighted by the literature (see Chen et al., 2015) adding a variable that measures the level of political risk and government transparency, such as the corruption index calculated by Transparency International, could be considered as an alternative direction for capturing additional elements.

[81] NS-rated banks refers to GSR assignments to banks with prior NSR assigned by S&P.

For the robustness tests, the interaction of country and year fixed effects are used, when suitable, in Eq. (4.1) to (4.6). The use of the interaction of country-year dummies considers time-varying observed and unobserved country heterogeneity.[82] Besides fixed effects, Chapter 4 also addresses any concerns on the heteroscedasticity and serial correlation in the error terms of the estimations by presenting two types of specifications. Specification (1) incorporates Huber-White heteroskedasticity standard errors to ensure the robustness of the standard errors (Huber, 1967; White, 1980). Specification (2) has cluster-robust standard errors, following the approach used by Cameron and Miller (2015). Hence, for Specification (2), the standard errors from the estimations of Eq. (4.1) to (4.6) are clustered at the bank level, to account for any within-bank correlation that has not been captured by the fixed effects.[83] The latter considers that in panel data estimations, the observations can be correlated across units (e.g. banks, cities, countries), and clustering by the unit would control that correlation.

Marginal effects (ME) are calculated for statistically significant variables for Eq. (4.1) to (4.6).[84] In nonlinear models, such as the probit models used in this Chapter, it is not possible to interpret the effect of the regressors on the dependent variable by analysing directly the value of the coefficients (Greene, 2012). MEs show the expected change in the dependent variable as a function of a change in one of the explanatory variables while the other covariates remain constant. In finance, MEs offers insights on the economic significance of the explanatory variables (Williams et al., 2013). According to Cameron and Trivedi (2010), there are three variants of MEs that can be estimated in binary models: the Average Marginal Effect (AME), the Marginal Effects at the representative Value (MER) and Marginal Effects at the Mean (MEM). In this Chapter, MEs are estimated using the STATA command "Margins" introduced by Williams (2012). For statistically significant binary regressors, the MEM for categorical variables show how P(Y=1) changes as the categorical variable changes from 0 to 1, holding all other variables constant at their sample means. For continuous regressors, the economic

[82] Interaction fixed effects are a common approach in the literature, to control for possible observed and unobserved macroeconomic and financial conditions, differences in development between countries of the sample and endogeneity concerns about omitted variables (Lemmon and Roberts, 2010; Thompson, 2011; Jiménez et al., 2012).
[83] Thompson (2011) suggests the use of double-clustering to obtain standard errors that are robust to simultaneous correlation in two dimensions, for example, across firms and time. However, when the sample is extremely unbalanced, Thompson suggests that single cluster is more appropriate than double-clustering. In the current study, the number of banks with GR or NR is reduced compared with the unrated banks, showing an extremely unbalanced sample. Hence, single clusters rather than double clusters are applied.
[84] Refers to coefficients with statistical significance at the 1, 5 and 10 percent levels.

significance of the variables is evaluated by calculating their elasticities (a 1% change), evaluated at the sample mean of the regressors.

4.5.2 Expected signs of the coefficient estimates

Section 4.4.2 presents the definition of the financial variables, while the characterisation of the other explanatory variables used in the estimations is discussed in Section 4.4.5. The current Section relates the selected variables to the literature review and indicates the rationale of the expected results of those variables (see the summary of the expected signs in Table 4.7).

$Size$: The selection of the variable is related to the issues of market segmentation and reputation value as discussed in Section 3.2.1. Prior literature suggests that bank size has a positive relation with bank credit ratings (e.g. Iannotta et al., 2006; Caporale et al., 2012; Shen et al., 2012). Larger banks display lower funding costs and can diversify risk more than smaller banks. In addition, larger banks have branches and subsidiaries or even own other non-financial businesses, which possibly grants them bargaining power with GRAs (fewer fees paid for ratings). Accordingly, it is expected that the *Size* coefficient has a positive sign in Eq. (4.1), Eq. (4.4) and Eq. (4.6). In contrast, for Eq. (4.2), (4.3) and (4.5) the *Size* coefficient is expected to be negative. In the case of Eq. (4.2), smaller size banks will benefit more from the certification effect of a GSR than larger banks, because the latter already gain reputation in the market. Hence, an increase in the size of larger banks will not improve the likelihood of GSR assignments. The argument follows Purda (2005), who finds a negative relation between the market capitalization and the stock returns of firms rated by the Canadian Bond Rating Service (CBRS), when S&P acquires CBRS, implying that smaller firms benefit much more from the acquisition as a result of S&P's certification effect. The argument by Purda (2005) also supports the negative expected sign of the *Size* coefficient in Eq. (4.3), if the reputation effect of NSR assigned by S&P decrease the funding costs of small banks with domestic operations compared to unrated banks.[85] From another perspective, GSR assignments are more likely in larger banks instead of NSR assignments. In Eq. (4.5), the justification for the negative expected sign is that GS-rated banks are already large banks, which usually have strong international ties. Thus, an increase in the bank size would probably not increase the likelihood of NSR assignments, as GSR assignments would be much more informative of their business.

[85] As the NSR is compared with other peer domestic banks, if the bank has better performance than them, the NSR would increase the chances of getting more local funding.

$Capitalratio$: The capital ratio is incorporated in the rating methodologies to assess the financial performance of the bank. It is expected that banks with lower capital have less resilience during a financial crisis, hence it can cause more reputation concerns to GRAs. A greater capital ratio implies higher capital strength, a buffer against unexpected fluctuations in the value of bank assets. Prior literature finds a positive relation between capital ratio and conservative banking practice, which leads to better ratings from a GRA (e.g. Bissoondoyal-Bheenick and Treepongkaruna, 2011; Caporale et al., 2012). In a study of Chinese corporates, Jiang and Packer (2017) find that higher leverage diminishes the probability of receiving a rating by a GRA against Chinese NRAs. Following these findings, the coefficient of *Capitalratio* is expected to be positive in Eq. (4.1) to (4.4) and (4.6). In contrast, the predicted sign of the coefficient of *Capitalratio* in Eq. (4.5) is negative, because GSR assignments are already informative to the domestic market, thus, it less likely that S&P assigns NSR additionally to GSR as a result of a capital increase.

$Netinterest$ ($Profitability$): The variable is related to the potential rating catering (see Section 3.2.2) of the GRAs. Profitability can be a decisive factor when deciding rating assignments because it may represent higher revenues for a GRA. Following Bae et al. (2013), it is expected that banks with better financial performance have global ratings. Hence, the coefficient in Eq. (4.1) to (4.4) and (4.6) should have a positive sign. In Eq. (4.5) the anticipated coefficient is negative because the profitability of GSR-rated banks usually outperforms NS-rated banks. Thus, the probability of S&P assigning an NSR to a GS-rated bank should decrease even if the profitability of the bank increases.

$NetLoanTA$ ($Liquidity$): Bank liquidity has become one of the most relevant aspects of evaluation in Basel III regulations. It is expected that banks with lower liquidity have more default risk. Hence, this can cause more reputation concerns to GRAs. As shown by Arena (2008) and Vazquez and Federico (2015), banks with weaker liquidity support are more vulnerable during a financial crisis and are assessed negatively by GRAs. For the current model, a higher $NetLoanTA$ implies a larger loan portfolio and less liquidity. Thus, a negative sign in the coefficient is expected in all equations.

$NPLratio$: The credit quality of the loan portfolio can have a significant weight in the rating because lending is usually the main activity for emerging market commercial banks. Any GRA that is concerned about its reputation can select banks with lower credit risk. Better quality loans reduce the banks’ credit risk (see Hau et al., 2013). Hence, it improves the likelihood of having a positive assessment from a GRA. Thus, a coefficient with a negative sign is expected in all equations.

$Efficiency$: According to S&P, the quality of earnings deteriorates as the cost to income ratio increases (S&P, 2011b). Banks with lower efficiency would have fewer incentives to pay the GRAs' fees. Hence, S&P would be more inclined to assign ratings to more efficient banks, linking this variable to the issue of reputation concern discussed in Section 3.2.1. According to Ferri and Liu (2003), highly-rated firms tend to have higher returns on capital and better operating efficiency. A higher ratio indicates lower efficiency and hence a negative assessment from S&P. Hence, the coefficient should have a negative sign in all equations.

$Trading$: If non-interest income is recurrent, it is assessed positively by S&P (S&P, 2011b). However, if it is not recurrent and has a significant weight in the total income, the bank's income might present large fluctuations under financial stress. Thus, this variable is related to GRAs' concerns on their reputation. It is expected that the sampled banks rely on interest income as their main source of revenue. However, if interest rates are low, banks tend to increase their non-interest income or fee income to generate revenues. Bertay et al. (2013) find that large size banks tend to rely more on non-interest income than on loans. Moreover, S&P bank rating methodology indicates that recurrent non-interest income is assessed positively in their rating as it reflects a stable business (S&P, 2011b). Hence, it is presumed that the coefficient of $Trading$ should have a positive sign in all equations.

$CostDebt$: Han et al. (2012) find that corporates' cost of debt tends to diminish if they are rated by GRAs. Hence, banks facing a higher cost of debt would be more likely to have ratings assigned by S&P to capture the certification effect. However, if the bank cannot rollover the debt and meet the interest payments, high levels of debt could be seen as risker by the GRA. Hence, an increase in the cost of the debt could have a positive or a negative influence on having an S&P rating, and the coefficient of $CostDebt$ could be either positive or negative in all equations.

Bonding: is a dummy variable that takes the value of one from the time that the bank is cross-listed or zero if it is only domestically listed or non-listed. Literature shows that cross-listed companies tend to exhibit better accounting standards (Bae et al., 2013; Di Pietra et al., 2014). As investors and CRAs perceive cross-listed as a positive characteristic, the expectation is a positive sign of the coefficient in all equations except in Eq. (4.5). In the latter case, cross-listed would not increase the probability of S&P assigning an NSR to GS-rated banks, because GSR is more informative for investors.

Ownership: is a dummy variable that takes the value of one if the country of origin of the global ultimate owner (GUO) is different from the bank's location. The likelihood of having a GSR assigned by S&P than being unrated or being an NSR-only bank is higher when the bank has foreign ownership. This is because GSR is useful if the bank is issuing overseas or wants to attract international portfolio investors, considering that GSR incorporate a reputation effect (see Han et al., 2012). Hence, a positive sign in the coefficient is expected in Eq. (4.1), (4.2), (4.4) and (4.6). However, in Eq. (4.3) and Eq. (4.5), the predicted sign of the *Ownership* coefficient is negative because banks with foreign ownership would perceive GSRs as more informative for investors and shareholders, hence, GS-rated banks would be less likely to have an NSR assigned by S&P.

$Moodys$ and $Fitch$: These two dummy variables are related to the effects of rating competition discussed in Section 3.2.3. In emerging economies, the demand for ratings is less significant than in advanced economies, as the capital markets are not developed and there are fewer investment instruments. Facing reduced investment options, the lack of depth of the financial market and opacity in the banking industry (Morgan, 2002) increases the probability of having a rating by multiple GRAs. Furthermore, prior ratings by any other GRA would inform S&P about the quality of information and the standards of domestic supervision, especially in emerging economies characterised by weak institutional and governance environment, which have a spillover effect on the banking sector (Chen et al., 2015; Toader et al., 2018). Thus, it is expected that an additional rating by Fitch and/or Moody's increases the likelihood of having a rating assigned by S&P.

Sovrating: The selection of this variable is related to the literature that highlights the strong link between sovereign risk and bank ratings in emerging economies (see Section 6.2). Williams et al. (2013) show that, in emerging economies, bank ratings are affected by the sovereign rating due to the sovereign ceiling effect. Ferri and Liu (2003) show that if the bank's GSR is too close to the sovereign rating, investors will not be able to differentiate between the credit risk of the bank and the country risk, affecting their investment decision. Following those arguments, in countries with a high risk of default, investors would find the information provided by GSR more useful, while in countries with low sovereign risk, NSR would be more informative. Accordingly, a high sovereign rating category would increase the likelihood of NSR assignments and decrease the probability of GSR assignments by S&P. Therefore, the expected sign of the coefficient is negative in Eq. (4.1), (4.2), (4.4) and (4.6) and positive in Eq. (4.3) and Eq. (4.5).

VIX: Higher volatility increases the risk of default. Thus, VIX is related to the reputation concerns of the GRAs when rating banks. Carvalho et al. (2014) show that the quality of GRAs' ratings increases in uncertain economic periods. As investors perceive ratings as a source of information and are more willing to lend to rated companies, in periods of high volatility S&P ratings should be more informative. Hence, it is expected that the VIX coefficient has a positive sign in all equations.

4.6 Empirical results

4.6.1 Drivers of bank ratings assigned by S&P

The estimations of Eq. (4.1) to Eq. (4.6) are presented in Tables 4.8 to 4.13, addressing the drivers of S&P bank rating assignments in emerging economies. As mentioned in Section 4.5.1, Eq. (4.1) to Eq. (4.4) incorporate country and year fixed effects and robust standard errors (Specification 1) and country and year fixed effects and standard errors clustered by bank (Specification 2). Eq. (4.5) and Eq. (4.6) include only year fixed effects and robust standard errors (Specification 1) and standard errors clustered by bank (see Section 4.5.1 for further details). As a general overview, the results indicate that bank size and competition between GRAs significantly influence S&P rating assignments. In all estimations, the variable *Size* has the expected sign and is highly significant. *Fitch* and *Moodys*, the proxies of competition included in Eqs. (4.1), (4.2), (4.4) and (4.5), are also highly significant. However, while *Moodys* coefficient has always the expected positive sign, *Fitch* coefficient has a negative sign except in Eq. (4.2), suggesting a substitution effect between Fitch and S&P ratings and complementary relation between S&P and Moody's ratings.

Table 4.8 presents the estimation of the determinants of NSR and GSR assignments by S&P (Eq. 4.1). The coefficient of *Size* variable is highly significant with the expected positive sign. This implies, the larger the bank size, the more likely are S&P rating assignments. The marginal effects suggest that on average, a 1% change in the natural log of *Size* at its mean, which is an increase from US$73,975 million to US$88,670 million, would increase the probability of S&P rating assignments by 4.65%. Since larger banks have a higher probability of participating in international stock exchanges (Schmukler and Claessens, 2007), indirectly, foreign interconnectivity of larger banks would also explain the strong impact of bank size on the probability of S&P rating assignments. The coefficient of *Trading* is also highly significant and has the expected positive sign, indicating that higher fee-based income banks are more likely to receive ratings from S&P. The results are also aligned with S&P's methodology, which assesses positively non-interest income when evaluating the bank's source of earnings (S&P, 2011b). If a bank's non-interest income increases by 1%, the probability of S&P rating assignments rises by 0.34%. The effects of competition between GRAs, measured by the dummy variables *Fitch* and *Moodys* is statistically significant. *Moody*'s coefficient has the expected positive sign and confirms that the probability of S&P rating assignments increases when Moody's also assigns ratings to the same bank. *Fitch* coefficient is significant and has an unexpected negative sign, when using robust standard errors. Thus, banks with ratings assigned by Fitch are less likely to receive S&P ratings. This may indicate that, instead of competition, Fitch rating assignments substitute S&P rating assignments in emerging economies. The MEs of *Fitch* are smaller than the MEs of Moody's. The probability of S&P rating assignments for a bank rated by Fitch decreases by 0.09% while it increases by 0.31% for banks with Moody's ratings. The coefficients of the control variables *Sovrating* and *VIX* have the expected sign, although only *VIX* is highly significant, indicating that S&P rating assignments are favoured during periods of uncertainty, which is consistent with the findings of Carvalho et al. (2014). Except for the coefficient of *Fitch*, which is not significant in Specification (2), the estimation results of Eq. (4.1) are robust when using clustered standard errors.

Table 4.9 shows the results of Eq. (4.2) and reports the drivers of GSR assignments by S&P for NS-rated banks.[86] In the estimation, *Size* coefficient is significant, and the sign supports the predictions. When *Size* rises from US$81,410 million to US$97,676 million[87], the probability of S&P assigning GSRs and NSRs compared to assigning only NSRs decreases by 6.82%. *Size* has the largest MEs of the estimation, highlighting its economic significance. The results could be showing that S&P is positioned as a strong competitor in NSR against domestic NRAs, when rating large institutions that could be associated with S&P's certification effect discussed in the literature (see Section 3.2.1), which might be also observed in NSR. The results are robust when using clustering (Specification (2)). The coefficients of *Capitalratio* and *Trading* are significant when using robust standard errors, although when clustering at the bank level, the coefficient of *Capitalratio* is no longer significant and *Trading* is significant at 10% level. The positive sign of *Trading* is consistent with the expectations and indicates that the probability of S&P assigning GSRs and NSRs instead of assigning only NSR is higher in banks with high non-interest fees. The positive and significant coefficients of *Bonding* and *Ownership* imply that international interconnectivity of the bank influences S&P's likelihood of assigning GSRs and NSRs, against only assigning NSRs. The MEs are larger for *Bonding.* The probability of assigning both NSR and GSR increases by 0.46% for cross-listed banks in comparison with non-listed or domestically listed banks. Moreover, *Fitch* and *Moodys* have the expected positive sign and are economically significant. If a bank has ratings assigned by Fitch (or Moody's), S&P probability of assigning both NSR and GSR compared to only assigning NSRs increases by 0.71% (0.74%). The different sign of *Fitch* coefficient in Eq. (4.2) compared to the other estimations, indicates that the effect of competition with Fitch on GSR

[86] The estimations of Eq. (4.2) includes observations with GSR and NSR assigned simultaneously and GSR assignments to NS-rated banks (with NSR assigned at any available date).
[87] An increase of 1% in the natural log of *Size* at its mean.

is strongly associated with NSR assignments by S&P (at the same time or before), confirming a significant and dynamic relation between NSRs and GSRs. The control variables have the expected sign, nevertheless, they are not significant. The estimates are robust when clustering at the bank level.

Table 4.10 reports the results of Eq. (4.3). NSR-only assignments by S&P can be jointly explained by bank characteristics: size, capital adequacy, liquidity and asset quality. The coefficients of all variables have the expected signs, except for *Capitalratio*. However, *Capitalratio* losses its significance when clustering at the bank level (Specification (2)). Thus, banks with a smaller size, high liquidity (i.e. lower *NetLoanTA* coefficient) and low credit risk (i.e. lower *NPLratio*) have a higher probability of receiving NSRs by S&P. The economic significance, indicated by the MEs, reveals that *Size* has a particularly strong effect on the likelihood of assigning NSRs against not being rated by S&P. On average, a 1% change in the natural log of *Size* at its mean, which is an increase from US$23,986 million to US$28,429 million, would decrease the probability of NSR assignments by 17.83%. The *NetLoanTA* coefficient also reveals that a 1% increase in the ratio of net loans to total assets (less liquidity in the portfolio) decreases the likelihood of NSR assignments by 3.77%. Unlike the other estimations, the control variable *Sovrating* is significant at 1%, which confirms that NSRs are favoured to GSRs in countries with higher sovereign ratings. A one-notch increase in the sovereign rating increases the likelihood of NSR assignments by 0.83%. The control variable *VIX* is also significant and has the anticipated sign, revealing that S&P NSR assignments are more likely when there is an increase in the global market risk sentiment. [88]

Table 4.11 presents the results of Eq. (4.4). The most relevant factor that influences GSR assignments by S&P is the *Size*. GSR assignments by S&P are more likely in larger banks than not being rated. *Size* has the highest economic significance among the variables of the estimation, with a 1% change in the natural log of Size at its mean, which is an increase from US$26,184 million to US$31,062 million, would increase the likelihood of S&P GSR assignments by 17.23%. Other bank characteristics that influence GSR assignments are *Net interest* and *Trading*, which have the anticipated sign and are statistically significant.[89] The dummy variable *Fitch* is only significant in Specification 1 and *Moodys* dummy variable is not

[88] In Eq. (4.3) the dummies *Bonding, Fitch and Moodys* are dropped because they predict the zero outcome perfectly.
[89] Eq. (4.4) does not include variables *Bonding* and *Ownership* because both predict perfectly the zero outcome in the dependent variable.

significant in any specification, indicating that competition does not influence GSR assignments by S&P.

Table 4.12 reports the estimations of Eq. (4.5), which examines the determinants of NSR assigned by S&P to GS-rated banks. It is worth noticing that the influence of the financial variables on the NSR assigned to GS-rated banks is similar to the effect of these variables on banks with only NSR (Eq. 4.3). *Size* coefficient is highly significant and has the expected negative sign. A 1% change in the natural log of *Size* at its mean, which is an increase from US$ 215,270 million to US$260,803 million,[90] decreases the likelihood of NSR assignments by 6.82% against GSR assignments. Similar to the results of Eq. (4.3), lower liquidity and lower credit quality reduce the probability of NSR assignments. The MEs of *NetLoanTA* have a greater magnitude than the MEs of *NPLrati*o, with a 1% increase in *NetLoanTA* (*NPL rati*o) reduces the probability of receiving an NSR from S&P by 2.25% (0.21%). The coefficient of *Costdebt* has a significant negative sign. The literature suggests that the cost of debt diminishes when a company has GSRs (e.g. Kisgen and Strahan, 2010; Han et al., 2012), which could explain why in the current setting NSR assignments in GSR-rated banks decreases when facing higher debt costs. The MEs indicate that a 1% increase in the cost of debt decreases the likelihood of NSR assignments by 0.74%. The coefficient of *Net interest* is significant at the 1% level when using robust standard errors; however, its relevance does not hold when using cluster-robust errors. The *Bonding* coefficient is significant and has a negative sign as expected. The MEs confirm that in GSR-rated banks, cross-listing decreases the probability of NSR assignments by S&P. Regarding the effects of competition between GRAs, both *Fitch* and *Moodys* dummy variables are significant at 5% when using robust standard errors, however, they become insignificant when clustering at the bank level. It is relevant to notice that *Fitch* has an unexpected negative coefficient as in Eq. (4.1), stressing the possibility of a substitution effect between GRAs.[91]

Table 4.13 presents the estimations of Eq. (4.6), which examines the drivers of GSR assignments in NS-rated banks. Like the previous cases, *Size* has the most significant coefficient and has the expected positive sign. The variable has high economic significance as a 1% change in the natural log of *Size* at its mean, which is an increase from US$ 5,013 million to US$5,850 million, increases the likelihood of GSR assignments by 33.3%. The coefficient

[90] Is relevant to notice that the average size of the banks with prior GSR is significantly higher than in the other samples used for the other equations.
[91] Eq. (4.5) only includes year fixed effects because when cluster-robust standard errors and country fixed effects are used, the results do not allow to derive statistically significant conclusions.

of *Efficiency* is also significant at the 5% level but has an unexpected positive sign. However, the coefficient loses its significance when standard errors are clustered at the bank level. However, the results of Eq. (4.6) should be considered carefully as the sample of GSR assignments on NS-rated banks corresponds only to banks in Mexico and Brazil. [92]

4.6.2 Robustness tests

As a robustness test, Equations (4.1), (4.2) and (4.4) are estimated using interacted year-country fixed effects,[93] to consider any unobservable variability across countries and across time simultaneously (see Table 4.14). Once the interacted fixed effects are incorporated, the results are similar to the results obtained before with Huber-White robust standard errors. Table 4.14 shows that *Size* coefficient is statistically significant and has the expected sign in all equations. However, when using year-country fixed effects, the magnitude of the *Size* coefficient in Eq. (4.2) and (4.4) increases, and the MEs in these two equations are more significant compared to the results from Specification (1) reported in Tables 4.9 and 4.11. Larger NS-rated banks are 7.58% less likely to have a GSR assigned by S&P (6.82%, in Table 4.9), while the probability of GSR assignments in larger unrated banks increases by 34.19% (21.44%, in Table 4.11). Likewise, with the inclusion of year-country fixed effects, the coefficients of *Fitch* and *Moodys* are highly significant in all equations and the MEs lead to similar results as Eq. (4.1), (4.2) and (4.4).

The second robustness test considers the period of the financial crisis (2007 – 2009) in the estimations of Eq. (4.1) to Eq. (4.6). There are two strands of literature on the influence of GRAs on firms during the financial crisis. One strand suggests that the reputation of GRAs decreased in comparison to domestic rating agencies during a financial crisis. Since ratings are not informative during those periods, GRAs cannot mitigate information asymmetries during a period of financial distress (e.g. Han et al., 2012). The second strand finds that credit ratings become more informative during a financial crisis (Hau et al., 2013). To consider the impact of the financial crisis, Eq. (4.1) to Eq. (4.6) incorporate the dummy variable *Crisis*, which takes the value of one during the global financial crisis (first quarter 2007 to fourth quarter 2009), and zero for the other quarters. Table 4.15 presents the results. Except for Eq. (4.4), where the *Crisis* coefficient is positive, the coefficient of the dummy variable is statistically significant

[92] In the Eq. (4.6) the variables *Bonding*, *Fitch* and *Moodys* are omitted because they predict the zero cases perfectly.
[93] Country-year fixed effects are not estimated for Eq. (4.3) to (4.5) because they only include year dummies to estimate fixed effects.

and has a negative sign. The results suggest that S&P rating assignments are less favoured by issuers during periods of financial distress. Nevertheless, the positive sign of *Crisis* in the estimation of Eq. (4.4) may suggest that GSR assignments are more likely than not being rated by S&P (or being rated by other GRA), suggesting the S&P GSR are still considered during a financial crisis.

A third robustness check considers the NSR rating category assigned in a previous quarter as a determinant of S&P assignments of GSR. In countries with high default risk, NSR at the highest rating category (AAA or near) contain little information for foreign investors as they do not reflect the sovereign risk, and GSR should be preferred in those cases. Thus, it is highly likely that S&P assigns GSR additional to NSR in high rating categories, or even that S&P replaces the NSR by a GSR. In contrast, in countries with low default risk, GSR should be less favoured, as these ratings are often bounded to the sovereign ceiling (e.g. see Borensztein et al., 2013; Williams et al., 2013; Almeida et al., 2017), while NSR can be used to select investments within the country. Figures 4.1 and 4.2 present preliminary evidence of these preferences. Figure 4.1 presents GSR assignments to NS-rated banks in the period of analysis (five banks in total). For all banks, NSR are at the investment grade one quarter before GSR assignments. The NSR is between 15 and 20 numerical ratings (equivalent to a rating range between A and AAA). Figure 4.2 presents the average NSR of banks with both NSR and GSR assignments compared to the average NSR in NSR-only banks. The figure shows that banks with both NSR and GSR assignments have superior NSR (and at an investment grade) than banks with only NSR assignments. Thus, Figures 4.1 and 4.2 suggest that NSR at the investment grade tends to influence GSR assignments by S&P.

Table 4.16 presents the results of Eq. (4.6) including the NSR lagged four quarters (*NSRprior*).[94] The lagged *NSR* coefficient is statistically significant and has the expected positive sign. The probability of GSR assignments by S&P after assigning NSRs rises by 0.03% if the NSRs increases one-notch. Thus, the robustness test confirms the important impact of NSR assignments on GSR assignments and suggests a relationship between NSR and GSR assigned by S&P.

In the fourth robustness test, alternative proxies of the financial variables are included, and the results are consistent with prior results (see Tables 4.17 to 4.19). In all tables, the common

[94] The robustness test is only applied to Eq. (4.6) because in that estimation, both outcomes (0 and 1) of the binary probit model include NS-rated banks. In contrast, Eq. (4.3), which is also focused on NSR, includes unrated banks as zero outcome in the binary probit model.

determinants of having a rating assigned by S&P are *Size* and the proxies of competition between GRAs: *Fitch* and *Moodys*. Table 4.17 shows that the ratio *NetLoanD* is not statistically significant in any estimation. In contrast, Table 4.18 shows that when an alternative proxy of liquidity (*LiqAssets*) is used, the coefficient is positive and highly significant in Eqs. (4.3) and (4.5). Thus, higher liquidity increases the likelihood of NSR assignments by S&P compared to unrated banks (Eq. 4.4) or compared to banks that have prior GSR assigned by S&P (Eq. 4.5). As *LiqAssets* is defined as the ratio of Liquid Assets to deposits and short-term funding, a positive sign in the coefficient is expected as stronger liquidity hedges against scenarios of financial distress. Table 4.19 includes *Tier 1* instead of *Leverage* as a proxy of capital adequacy, *ROAA* instead of *NetInt* and includes also *LiqAssets.* The most significant coefficient among those three is *LiqAssets*, which is positive as expected when S&P assigns initial NSR or GSR or assigns NSR to GS-rated banks.

4.7 Conclusions

The key aim of this Chapter is to investigate the drivers of both NSR and GSR rating assignments for banks in emerging economies. A sample of 145 banks from 10 emerging economies[95] rated at the national and global scale by S&P for 2006 to 2015 is employed. To study the dynamics between GSR and NSR assigned by S&P, the Chapter tests five sub-hypotheses that address the drivers of S&P ratings, acknowledging the possibility of having both types of ratings assigned simultaneously or in different periods by S&P.

The study of the determinants of NSR and GSR assigned by GRAs in emerging economies is relevant because of the expansion of the rating activity of GRAs in recent years. There are a growing number of studies that examine the impact of GRA rating changes compared with NRAs (Ferri et al., 2013; Jiang and Packer, 2017, 2019; Joe and Oh, 2017; Yang et al., 2017; Livingston et al., 2018; Hu et al., 2019; Oh and Kim, 2019), given the important growth of GRAs through affiliates and joint ventures, arguably because regulation has discouraged the establishment of subsidiaries (e.g. Korea, China). The results of these studies show that GRAs' domestic ratings contain valuable information for investors, implying that GRAs are strong competitors of NRAs in those ratings. However, the available research is scarce, focused on Asian countries and often corresponds to country-specific studies that address either GSR or NSR, while the dynamic between the two types of ratings has not been explored by the literature. This Chapter has a unique focus by studying the drivers and dynamics of those ratings in a cross-country setting. A probit modelling approach is employed to consider the bank's likelihood of having a national (global) rating against not being rated or having a global (national) rating.

The key finding of the Chapter is that the bank's size and the competition between GRAs have the strongest influence on the probability of S&P rating assignments and are the main drivers of NSR and GSR assignments, supporting Hypothesis *H1*. Both types of rating assignments are more likely for large banks, which suggests the presence of market segmentation (see Ferri and Lacitignola, 2010), which is aligned with Hypothesis *H1d* and *H1e*. Namely, GRAs would typically assign ratings to large banks, supporting Hypothesis *H1a and H1c*, while smaller banks would be covered by NRAs, supporting Hypothesis *H1b*. Nonetheless, other GRAs could be assigning ratings to smaller banks, in which case the market segmentation would occur

[95] Argentinean banks are excluded from the sample rated by S&P because their financial and accountant information does not match any S&P ratings in ID-CREM. However, they are included in the sample not rated by S&P and used in Eq. (4.1), (4.3) and (4.4).

between S&P and the other GRAs. The results of the inclusion of Fitch and Moody's dummy variables suggest that Fitch is S&P's competitor, while Moody's tends to assign ratings to the same banks. The results for the sub-samples show that the magnitude and the direction of the effect of bank size depend on the type of rating assigned by S&P (NSR or GSR) and whether the bank has prior S&P ratings or not. Thus, the estimations support the sub hypotheses which address the potential dynamic between NSR and GSR.

To a lesser extent, ratings assigned by S&P are also driven by higher credit quality, liquidity, and higher non-interest income. Thus, the results show that the banks' financial performance has a strong effect on S&P rating assignments, suggesting that reputation concerns could be driving these assignments. One downside of this finding is that it can lead to rating inflation (see Efing and Hau, 2015) for two reasons: i) GRAs can assume those banks have a lower probability of default, and ii) these large institutions can contribute significantly to the GRAs' fees. Additionally, S&P rating assignments are also related to the type of ownership. NSR assignments are more likely in banks operating at the domestic level, while foreign ownership and cross-listing increase the probability of GSR assignments. These findings highlight the relevance of bonding (see Di Pietra et al., 2014) when assigning GSRs and the potential competition between S&P and NRAs in emerging economies.

The results also show that NSR assignments by S&P occur more often in countries with higher sovereign ratings, while unrated banks located in countries with high sovereign risk have a greater likelihood of GSR assignments. Thus, the Chapter highlights that GSR assignments incorporate less information on the bank risk than NSR assignments when the sovereign risk is low, while GSR assignments are more valuable for international investors when the sovereign risk is high. These findings show how influential are sovereign ratings on bank ratings in emerging economies and the strong effect of the sovereign ceiling in GSR assignments, confirming the findings reported in Williams et al. (2013) and Huang and Shen (2015). They also suggest a strong relation between NSRs and sovereign ratings, which has not been discussed in prior literature. The Chapter also shows that the rating category of prior NSR assignments is a relevant determinant of receiving a GSR, which emphasises that NSR are a fundamental part of GRAs' rating business, an aspect that has been studied scarcely and only for China (see Livingston et al., 2018). A new direction of research could be the analysis of the effect of changes in the sovereign ratings on future changes in NSR. Furthermore, when considering the financial crisis in the analysis, having GSR and NSR assigned by S&P is less likely. Thus, the analysis of the information content of NSR and GSR assignments by GRAs during periods of distress is also a potential research topic in the future.

The evidence in this Chapter supports the existence of a dynamic association between NSRs and GSRs assigned by S&P for banks in emerging economies. GSR assignments are less likely in larger NS-rated banks, NSR assignments in small banks increase the probability of GSR assignments. One limitation of the results is the small sample size which is used to examine NSR-only or GSR-only assigned by S&P (i.e. Equations (4.3) and (4.4)). The limitation is also relevant when examining NS-rated banks with GSR assigned during the period of analysis (Equation (4.6)). To improve the reliability of the statistical inference, initial bank ratings assigned by S&P before and after the third quarter of 2006 are added to Eqs. (4.3), (4.4) and (4.6). Moreover, the sample of not-rated banks is also included, increasing considerably the sample size. Although these additions do not eliminate the risk of potential sample bias in those equations, the findings are aligned with the prior expectations.

The results of Chapter 4 open potential avenues for future research, as this would suggest that investors grant NSR a certification effect, highlighted by other literature which studies GSRs only (Kisgen and Strahan, 2010; Han et al., 2012; Bae et al., 2013). Likewise, as larger banks have systematic relevance in an economy (Vazquez and Federico, 2015), their NSRs also would provide important signals regarding the country's financial stability. As NSR assignments are more common in large banks, the quality of those ratings and the review of the GRAs' practice in emerging economies should be subject to stronger scrutiny by regulators, similar to the study undertaken by regulators in Europe (European Commission, 2015).

The information restrictions on NSR assigned by NRAs not only concerns independent NRAs but also NSR assigned by NRAs with joint ventures or partnerships with GRAs. The latter institutions have their rating standards, criteria, and methodologies. Therefore, their ratings are independent opinions that are not linked to GRAs and therefore, similar to the independent NRAs, obtaining historical data is very difficult. However, these types of ratings should be considered in future academic research due to the relevance of NRAs in the credit rating industry and the significant void in the literature regarding NSRs. Some aspects that deserve further attention are: i) the influence of sovereign rating actions on NSR assignments, ii) the information content of NSR in the capital markets, iii) the influence of current NSR level on NSR rating migrations, and iv) the effects of competition between NRAs on NSR.

NRAs can only assign NSR and they are not authorised to offer GSR. Accordingly, NRAs are not included in Chapter 4 because the objective is to analyse the determinants of NRS and GRS and the dynamics of both ratings. Nevertheless, the literature shows that comparing NSR from NRAs and GSR from GRAs is possible, despite the differences in the rating categories, by transforming the NSR to a rating scale equivalent to GSR (see Jiang and Packer, 2017, 2019). One aspect to consider, however, is that these studies also highlight that even after the transformation, the ratings assigned by GRAs seem to be lower than the ratings assigned by NRAs, suggesting that GRAs and NRAs do not have equivalent scales even after the transformation. The same conclusion is also reached when evaluating NSR assigned by independent NRAs compared to NRAs with partnerships or joint ventures with GRAs (see Livingston et al., 2018). These differences between GRAs and NRAs also explain why this thesis does not incorporate NRAs as a means of comparison with GRAs.

The strong dynamic between NSR and GSR assignments also contrasts with prior literature that shows NSR and GSR as independent rating decisions by GRAs (Ferri and Liu, 2003). This offers an alternative to future studies examining the influence of GRAs' rating assignments on bank share prices or bond yields in a cross-country setting. Prior research has only investigated the effect of NSRs assigned by GRAs' affiliates on bond yields of Chinese corporates (Livingston et al., 2018) and the impact of GSR assigned by GRAs on bond yields of Chinese corporates (Jiang and Packer, 2019).

The results also highlight how influential are sovereign ratings on bank ratings in emerging economies and the strong effect of the sovereign ceiling in GSR assignments, confirming the findings reported in Williams et al. (2013) and Huang and Shen (2015). GSR assignments are less favoured than NSR assignments when the sovereign risk is low and preferred by international investors when the sovereign risk is high. Thus, a new direction of research could be the analysis of the effect of changes in the sovereign ratings on future changes in NSR. Furthermore, when considering the financial crisis in the analysis, having GSR and NSR assigned by S&P is less likely. Thus, the analysis of the informational content of NSR and GSR assignments by GRAs during periods of distress is also a potential aspect to research in the future.

Regarding the competition between GRAs, the results suggest that Fitch ratings potentially substitute S&P rating assignments in banks from emerging markets, implying that investors might perceive differences in the rating assignments between GRAs. The market impact of having multiple ratings has been examined in previous literature, focusing on the disagreements between the GSRs assigned by GRAs (e.g. Livingston and Zhou, 2016). However, the market impact of NSR assigned by multiple GRAs could be the subject of future research. For regulators, the results on competition regarding the NSRs assigned by S&P are also relevant, as they would indicate that competition between GRAs in NSR can potentially decrease the quality of these ratings, which offers an argument for stronger supervision of GRAs. For investors, the effect of competition on NSRs reveals the risk of relying only on the ratings by GRAs to assess their investment instead of developing their own independent analysis.

Chapter 4 Tables

Table 4.1 Availability of rating information in ID-CREM database

	NSR data		GSR data	
Country	*Starting quarter*	*Final quarter*	*Starting quarter*	*Final quarter*
Argentina (AR)	Jul-06	Oct-15	Jul-06	Oct-15
Brazil (BR)	Jul-06	Oct-15	Jul-06	Oct-15
China (CN)	Jul-11	Oct-15	Oct-08	Oct-15
Colombia (CO)	N/A	N/A	Oct-08	Oct-15
Indonesia (ID)	Jul-09	Oct-15	Oct-08	Oct-15
Kazakhstan (KZ)	Jul-06	Oct-15	Jul-06	Oct-15
Mexico (MX)	Jul-06	Oct-15	Jul-06	Oct-15
Nigeria (NG)	Apr-09	Jul-15	Oct-08	Oct-15
Russia (RU)	Jul-06	Oct-15	Jul-06	Oct-15
South Africa (ZA)	Jan-07	Oct-15	Jul-06	Oct-15
Thailand (TH)	Jul-09	Oct-15	Oct-08	Oct-15

The table presents the initial and final quarters with available rating data per country collected from ID-CREM database for the period October 2006 to December 2015. NSR stands for national scale ratings and GSR stands for global scale ratings.

Table 4.2 Summary of the final sample

Concept	Terminology	Number of Banks
Initial sample from Bankscope (2005 - 2016)	*Initial sample*	1672 banks
Banks with quarterly financial information after trimming (2006Q3-2015Q4)	*Trimmed sample*	420 banks
Banks from the initial sample (420) that matched ID-CREM ratings (2006Q3-2015Q4)	*Matched sample*	145 banks
Banks without ratings in ID-CREM	*Unrated sample*	275 banks
Banks from the matched sample that have only NSR (2006Q3-2015Q4)	*NSR-only banks*	10 banks from the sample of 145 banks
Banks from the matched sample that have only GSR (2006Q3-2015Q4)	*GSR-only banks*	5 banks from the sample of 145 banks
Banks from the matched sample that have both NSR and GSR assigned on the same date (2006Q3-2015Q4)	*NSR-GSR banks*	52 banks from the sample of 145 banks
Banks from the matched sample that have NSR prior 2006Q3[a]	*NS-rated banks*	38 banks from the sample of 145 banks
Banks from the matched sample that have GSR prior 2006Q3[b]	*GS-rated banks*	56 banks from the sample of 145 banks

The table reports the number of banks after trimming the financial data and matching it with the rating data for the period July 2006 to December 2015 (2006Q3 – 2015Q4). ***a.*** *From the 38 NS-rated banks, S&P assigned GSR to 3 banks after July 2006.* ***b.*** *From the 56 GS-rated banks, S&P assigned NSR to 26 banks after July 2006.*

Table 4.3 Variables' definitions and data sources

Symbol	Units	Definition	Source
Size	($) LN	Natural Logarithm of book value of total assets	Bankscope
Leverage	%	Equity / Total Assets	Bankscope
ROAA	%	Return on Average Assets (ROAA)	Bankscope
Tier1	%	Tier 1 Ratio	Bankscope
Capitalratio	%	Total Capital Ratio	Bankscope
NetLoanTA	%	Net Loans / Total Assets	Bankscope
NetLoanD	%	Net loans / Deposits and short-term funding	Bankscope
LiqAssets	%	Liquid Assets / Deposits and short-term funding	Bankscope
NPLratio	%	Impaired Loans (NPLs) / Gross Loans	Bankscope
Netint	%	Net Interest Income / Average Earning Assets	Bankscope
Efficiency	%	Cost to Income Ratio	Bankscope
Trading	%	Non-Interest Income / Gross Revenues	Bankscope
Bonding	{0,1}	Dummy variable: 1 if the bank is listed in one or more foreign stock exchanges; 0 otherwise	Bankscope, CapitalIQ
Costdebt	%	Interest expenses / average interest-bearing liabilities	Bankscope
Ownership	{0,1}	Dummy variable: 1 if the bank has foreign ownership; 0 otherwise	Bankscope
Fitch	{0,1}	Dummy variable: 1 if the bank has NSR or GSR assigned by Fitch in the same year S&P assigns a GSR; 0 otherwise	ID-CREM, Fitch, CapitalIQ
Moodys	{0,1}	Dummy variable: 1 if the bank has NSR or GSR assigned by Moody's in the same year S&P assigns a GSR; 0 otherwise	ID-CREM, Moody's, CapitalIQ
SovRating	1 - 20	Average of the quarterly sovereign ratings assigned by S&P, Moody's and Fitch, based on the 20-point numerical scale (taking values from 1 to 20)	ID-CREM, Fitch, Moody's, CapitalIQ
VIX	Index	Implied volatilities of a wide range of S&P 500 index options	Chicago Board Options Exchange

The table presents the definition, description and data sources of the financial variables from the trimmed sample (420 banks from 11 emerging economies) for the period July 2006 to December 2015. Obs. stands for observations, Std. Dev. is standard deviation.

Table 4.4 Summary statistics of the sampled banks (trimmed sample)

Variable	Obs.	Mean	Std. Dev.	Min	P25	Median	P75	Max
Size	4,284	15.72	2.06	10.58	14.31	15.57	17.13	21.68
Leverage	4,284	12.38	6.57	2.31	7.91	10.72	14.86	49.61
ROAA	4,284	1.35	1.83	-9.97	0.69	1.23	1.97	13.88
Tier1	4,284	14.96	6.76	4.54	10.74	13.20	16.99	65.53
Capitalratio	4,284	17.35	6.27	7.56	13.72	15.71	18.87	66.80
NetLoanTA	4,284	55.78	17.72	3.22	45.38	59.24	68.67	91.86
NetLoanD	4,284	87.65	61.42	6.26	60.67	79.31	95.20	659.14
LiqAssets	4,284	35.38	26.84	0.28	18.23	28.71	44.49	259.38
NPLratio	4,284	5.72	6.62	0.09	1.80	3.61	7.25	65.43
Netint	4,284	7.18	7.49	0.51	3.34	5.05	7.58	68.84
Efficiency	4,284	56.23	20.49	15.59	43.05	53.76	66.52	196.47
Trading	4,284	25.65	18.77	-50.03	13.59	24.24	35.26	94.32
Bonding	4,284	0.16	0.37	0.00	0.00	0.00	0.00	1.00
Costdebt	4,284	6.51	5.64	-13.60	3.46	5.50	8.35	231.58
Ownership	4,284	0.73	0.44	0.00	0.00	1.00	1.00	1.00
Fitch	4,284	0.39	0.49	0.00	0.00	0.00	1.00	1.00
Moodys	4,284	0.26	0.44	0.00	0.00	0.00	1.00	1.00
SovRating	4,284	11.94	1.94	4.00	11.00	12.00	13.00	17.00
VIX	4,284	20.84	10.24	11.03	14.83	17.03	23.07	58.60

The table presents the summary statics of the financial variables from the trimmed sample (420 banks from 11 emerging economies) for the period July 2006 to December 2015. For the definition of the variables see Sections 4.4.2 and 4.4.5. Obs. stands for observations, Std. Dev. is standard deviation.

Table 4.5 Pairwise correlations

Panel A. *Pairwise correlation - Sample used in Eq. (4.1)*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Size (1)	1													
Capitalratio (2)	-0.42	1												
Net interest (3)	-0.34	0.18	1											
NetLoanTA (4)	-0.14	-0.16	0.07	1										
NPL ratio (5)	-0.22	0.13	0.32	-0.02	1									
Efficiency (6)	-0.42	0.11	0.12	-0.11	0.13	1								
Trading (7)	0.07	-0.02	-0.25	-0.24	-0.04	0.04	1							
Cost of debt (8)	-0.30	0.13	0.28	-0.05	0.16	0.18	-0.11	1						
Bonding (9)	0.24	-0.08	-0.06	0.04	-0.05	-0.06	0.01	-0.05	1					
Ownership (10)	0.07	-0.01	0.04	-0.09	0.02	-0.01	0.03	-0.03	-0.04	1				
Fitch (11)	0.27	-0.15	-0.15	0.00	-0.04	-0.11	0.07	-0.08	0.12	0.03	1			
Moodys (12)	0.32	-0.17	-0.12	0.07	0.00	-0.15	-0.02	-0.07	0.08	0.06	0.39	1		
Sovrating (13)	0.44	-0.22	-0.09	-0.14	-0.05	-0.29	0.10	-0.21	-0.17	0.11	0.04	0.15	1	
Vix (14)	-0.05	0.07	0.03	0.00	0.04	0.00	-0.03	0.11	-0.04	-0.03	-0.03	0.00	0.10	1

Panel B. *Pairwise correlation - Sample used in Eq. (4.2)*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Size (1)	1													
Capitalratio (2)	-0.34	1												
Net interest (3)	-0.26	0.29	1											
NetLoanTA (4)	-0.21	0.02	0.33	1										
NPL ratio (5)	-0.07	0.08	0.20	0.15	1									
Efficiency (6)	-0.32	0.05	0.00	-0.20	-0.02	1								
Trading (7)	-0.10	-0.03	-0.29	-0.34	-0.05	0.17	1							
Cost of debt (8)	-0.19	0.15	0.34	0.06	0.26	0.19	-0.10	1						
Bonding (9)	0.33	-0.05	-0.01	0.08	-0.05	0.04	-0.05	-0.09	1					
Ownership (10)	0.18	-0.04	-0.07	-0.23	-0.08	0.05	-0.09	-0.05	0.17	1				
Fitch (11)	0.23	-0.09	-0.05	0.05	0.00	-0.06	-0.07	-0.04	0.22	0.09	1			
Moodys (12)	0.22	-0.12	-0.06	0.11	0.09	-0.14	-0.19	0.07	0.05	-0.18	0.54	1		
Sovrating (13)	0.26	-0.31	-0.22	-0.09	-0.24	-0.23	0.01	-0.31	-0.04	0.07	-0.02	-0.07	1	
Vix (14)	-0.08	0.19	0.05	0.00	0.01	0.00	-0.03	0.18	-0.01	-0.03	-0.17	-0.13	0.03	1

Panel C. *Pairwise correlation - Sample used in Eq. (4.3)*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Size (1)	1													
Capitalratio (2)	-0.40	1												
Net interest (3)	-0.30	0.16	1											
NetLoanTA (4)	-0.12	-0.15	0.08	1										
NPL ratio (5)	-0.25	0.14	0.43	-0.07	1									
Efficiency (6)	-0.37	0.05	0.09	-0.16	0.13	1								
Trading (7)	0.07	-0.02	-0.24	-0.28	-0.07	0.07	1							
Cost of debt (8)	-0.24	0.10	0.24	-0.05	0.17	0.13	-0.09	1						
Bonding (9)	0.39	-0.10	-0.08	0.09	-0.10	-0.11	0.01	-0.09	1					
Ownership (10)	-0.06	-0.01	0.08	-0.08	0.04	0.04	0.04	-0.01	-0.07	1				
Fitch (11)	0.42	-0.16	-0.16	0.04	-0.07	-0.19	0.09	-0.09	0.11	0.04	1			
Moodys (12)	0.22	-0.13	-0.03	0.07	-0.03	-0.12	-0.05	0.01	0.09	0.09	0.41	1		
Sovrating (13)	0.35	-0.15	-0.02	-0.19	0.02	-0.23	0.14	-0.13	-0.10	0.08	0.11	0.08	1	
Vix (14)	-0.07	0.07	0.04	0.01	0.06	-0.02	-0.04	0.13	-0.04	-0.03	0.01	0.03	0.12	1

(Continued on next page)

Table 4.5 (Continued)

Panel D. *Pairwise correlation - Sample used in Eq. (4.4)*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Size (1)	1													
Capitalratio (2)	-0.40	1												
Net interest (3)	-0.30	0.14	1											
NetLoanTA (4)	-0.11	-0.19	0.03	1										
NPL ratio (5)	-0.25	0.13	0.40	-0.09	1									
Efficiency (6)	-0.38	0.06	0.09	-0.15	0.15	1								
Trading (7)	0.10	-0.02	-0.23	-0.23	-0.06	0.03	1							
Cost of debt (8)	-0.25	0.10	0.24	-0.07	0.16	0.13	-0.09	1						
Bonding (9)	0.39	-0.12	-0.10	0.08	-0.06	-0.11	0.02	-0.09	1					
Ownership (10)	-0.06	-0.01	0.07	-0.07	0.06	0.05	0.05	-0.01	-0.07	1				
Fitch (11)	0.40	-0.18	-0.20	-0.01	-0.06	-0.18	0.13	-0.10	0.09	0.07	1			
Moodys (12)	0.22	-0.13	-0.03	0.03	0.00	-0.12	-0.02	0.01	0.09	0.10	0.37	1		
Sovrating (13)	0.36	-0.15	0.01	-0.16	0.05	-0.25	0.12	-0.13	-0.10	0.09	0.16	0.12	1	
Vix (14)	-0.06	0.06	0.03	0.00	0.04	-0.02	-0.04	0.12	-0.05	-0.02	0.00	0.01	0.12	1

Panel E. *Pairwise correlation - Sample used in Eq. (4.5)*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Size (1)	1													
Capitalratio (2)	-0.52	1.00												
Net interest (3)	-0.41	0.36	1.00											
NetLoanTA (4)	-0.28	-0.08	0.13	1.00										
NPL ratio (5)	-0.41	0.21	0.11	0.10	1.00									
Efficiency (6)	-0.49	0.19	-0.05	0.02	0.20	1.00								
Trading (7)	-0.12	0.12	-0.08	0.03	-0.12	0.15	1.00							
Cost of debt (8)	-0.52	0.26	0.53	-0.09	0.20	0.16	-0.04	1.00						
Bonding (9)	-0.16	-0.01	0.13	-0.16	0.09	0.02	-0.21	0.41	1.00					
Ownership (10)	0.32	-0.10	-0.37	-0.16	0.02	-0.03	0.25	-0.41	-0.20	1.00				
Fitch (11)	-0.03	-0.10	-0.16	-0.06	0.03	0.12	-0.02	0.03	0.02	-0.11	1.00			
Moodys (12)	0.24	-0.09	-0.07	0.03	0.00	-0.12	0.05	-0.07	-0.04	0.14	0.22	1.00		
Sovrating (13)	0.66	-0.33	-0.38	0.02	-0.17	-0.28	-0.06	-0.50	-0.53	0.32	-0.08	0.33	1	
Vix (14)	0.02	-0.05	0.00	-0.02	0.00	0.00	-0.08	-0.02	-0.03	0.01	0.03	0.03	0.06	1

Panel F. *Pairwise correlation - Sample used in Eq. (4.6)*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Size (1)	1														
Capitalratio (2)	-0.46	1													
Net interest (3)	-0.40	0.56	1												
NetLoanTA (4)	-0.48	0.15	0.42	1											
NPL ratio (5)	-0.10	0.08	0.15	0.10	1										
Efficiency (6)	-0.30	-0.01	-0.02	-0.16	-0.12	1									
Trading (7)	0.03	0.04	-0.27	-0.40	-0.15	0.22	1								
Cost of debt (8)	-0.19	0.12	0.21	0.14	0.21	0.03	-0.05	1							
Bonding (9)	0.08	0.07	0.36	0.05	-0.07	0.08	-0.04	-0.08	1						
Ownership (10)	0.11	-0.15	-0.04	-0.28	-0.05	0.08	-0.14	-0.10	0.08	1					
NSR (11)	0.57	-0.06	-0.15	-0.14	0.02	-0.56	0.02	-0.09	0.15	-0.11	1				
Fitch (12)	0.29	-0.12	-0.09	0.01	-0.11	-0.24	-0.11	-0.14	-0.04	0.08	0.33	1			
Moodys (13)	0.29	-0.12	-0.09	0.01	-0.11	-0.24	-0.11	-0.14	-0.04	0.08	0.33	1.00	1		
Sovrating (14)	0.09	-0.22	-0.17	-0.07	-0.03	0.08	0.06	-0.07	-0.03	-0.09	0.15	0.02	0.02	1	
Vix (15)	-0.07	0.11	0.03	0.01	0.05	0.07	-0.04	0.24	0.00	0.01	0.04	-0.09	-0.09	0.27	1

The table reports in each panel the pairwise correlation matrix between the variables used in each equation (Panel A: Eq. (4.1); Panel B: Eq. (4.2); Panel C: Eq. (4.3); Panel D; Eq. (4.4); Panel E: Eq. (4.5); Panel F: Eq. (4.6)). Panel F includes the NSR lagged four quarters, which is used in the robustness checks.

Table 4.6 Summary of the samples used in equations (4.1) to (4.6)

Research question	Hypothesis	Equation	Ordinal value[a]	Definition of the dependent variable	The period when S&P assigns the rating	Obs.
What are the drivers of banks' rating assignments by S&P in emerging economies?	H1	Eq. (4.1)	1	NSR and/or GSR assignments by S&P	Rating assignments after 2006Q3.	2,349
			0	**Unrated banks**		
What factors influence whether S&P assigns global scale ratings at the same time or after assigning national bank ratings to banks?	H1(a)	Eq. (4.2)	1	GSR assigned by S&P (including observations where S&P assigns GSR and NSR simultaneously or assigns GSR after assigning NSR before 2006Q3)	GSR assignments after 2006Q3, NSR assigned at any available date	608
			0	**NSR-only assignments by S&P**		
What factors influence whether banks have only national scale ratings assigned by S&P?	H1(b)	Eq. (4.3)	1	NSR-only assignments by S&P	NSR assignments by S&P at any available date	1,542
			0	**Unrated banks**		
What factors influence whether banks have only global scale ratings assigned by S&P	H1(c)	Eq. (4.4)	1	GSR-only assignments by S&P	GSR assignments by S&P at any available date	1,462
			0	**Unrated banks**		
For global-rated banks what are the determinants of having national scale ratings assigned by S&P?	H1(d)	Eq. (4.5)	1	S&P NSR assignments to GS-rated banks	NSR assignments after 2006qQ. GSR assignments at any available date	468
			0	**GSR-only assignments by S&P**		
For national-rated banks what are the determinants of having global scale ratings assigned by S&P?	H1(e)	Eq. (4.6)	1	S&P GSR assignments to NS-rated banks	GSR assignments after 2006Q3. NSR assignments at any available date	186
			0	**NSR-only assignments by S&P**		

The table presents a summary of the sample used in the probit model specifications presented in Eqs. (4.1) to (4.6) for the NSR and GSR assigned by S&P during the period July 2006 to December 2015 (2006Q3-2015Q4). ***a.*** *Ordinal value corresponds to the outcome of the binary probit model. Unrated banks are included if they have financial data between 2006Q3-2015Q4.*

Table 4.7 Expected signs of the coefficient estimates

	Eq. (4.1)	*Eq. (4.2)*	*Eq. (4.3)*	*Eq. (4.4)*	*Eq. (4.5)*	*Eq. (4.6)*
Explanatory variables	H1	H1(a)	H1(b)	H1(c)	H1(d)	H1(e)
Size	+	-	-	+	-	+
Capital ratio	+	+	+	+	-	+
Net interest	+	+	+	+	-	+
NetLoanTA	-	-	-	-	-	-
NPL ratio	-	-	-	-	-	-
Efficiency	-	-	-	-	-	-
Trading	+	+	+	+	+	+
Cost of debt	+ / -	+ / -	+ / -	+ / -	+ / -	N/A
Bonding	+	+	N/A	N/A	-	N/A
Ownership	+	+	-	N/A	-	N/A
Fitch	+	+	N/A	+	+	N/A
Moodys	+	+	N/A	+	+	N/A
Sovrating	-	-	+	-	+	-
Vix	+	+	+	+	+	+

The table presents the expected sign on each of the variables used in the estimations of Eqs. (4.1) to (4.6). See Section 4.4.2 for the definition of the variables and Section 4.5.2 for the rationale of the signs of the variables.

Table 4.8 The determinants of S&P rating assignments - Eq. (4.1)

	Dependent variable: *SPrating*		
Variable	(1)	(2)	ME(%)
Size	0.22***	0.22***	4.65
	(8.62)	(2.80)	
Capitalratio	0.01	0.01	
	(0.85)	(0.45)	
Net interest	0.00	0.00	
	(0.12)	(0.05)	
NetLoanTA	0.00	0.00	
	(1.63)	(0.62)	
NPLratio	-0.01	-0.01	
	(-0.99)	(-0.46)	
Efficiency	-0.00	-0.00	
	(-1.20)	(-0.57)	
Trading	0.01***	0.01**	0.34
	(4.36)	(2.04)	
Costdebt	0.00	0.00	
	(0.19)	(0.12)	
Bonding	0.16	0.16	
	(1.51)	(0.47)	
Ownership	-0.01	-0.01	
	(-0.12)	(-0.04)	
Fitch	-0.33***	-0.33	-0.09
	(-4.45)	(-1.54)	
Moodys	0.99***	0.99***	0.31
	(13.05)	(4.79)	
Sovrating	-0.00	-0.00	
	(-0.03)	(-0.03)	
VIX	0.02***	0.02***	0.49
	(2.65)	(2.58)	
Observations	2,349	2,349	
Pseudo R-squared	27.1%	27.1%	
Country FE	YES	YES	
Year FE	YES	YES	

*The table presents the results of the probit model used in Eq. (4.1). The dependent variable **SPrating** takes the value of one from the quarter S&P assigns a rating (NSR or GSR or both), onwards, and zero if the bank is not rated by S&P. Robust z-statistics in parenthesis. Specification (1) includes robust standard errors. Specification (2) includes robust standard errors clustered at the bank level. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. See Tables 4.3, 4.4 and 4.6 for details on the data sample. A full set of country and year dummies are included in both Specifications (1) and (2). The Marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 4.5.1.*

Table 4.9 The determinants of GSR assignments by S&P at the same time or after NSR assignments - Eq. (4.2)

	Dependent variable: *GSRandNSR*		
Variable	(1)	(2)	ME(%)
Size	-0.52***	-0.52***	-6.82
	(-5.57)	(-3.57)	
Capitalratio	-0.04**	-0.04	-0.51
	(-2.06)	(-1.57)	
Net interest	0.00	0.00	
	(0.02)	(0.01)	
NetLoanTA	-0.00	-0.00	
	(-0.71)	(-0.42)	
NPLratio	0.00	0.00	
	(0.24)	(0.16)	
Efficiency	-0.00	-0.00	
	(-0.14)	(-0.09)	
Trading	0.02***	0.02*	0.37
	(3.64)	(1.89)	
Costdebt	-0.03	-0.03	
	(-1.20)	(-0.93)	
Bonding	1.34***	1.34**	0.46
	(3.88)	(2.22)	
Ownership	0.60***	0.60	0.23
	(2.73)	(1.59)	
Fitch	2.76***	2.76***	0.71
	(4.54)	(3.92)	
Moodys	2.73***	2.73***	0.74
	(7.32)	(3.77)	
Sovrating	-0.06	-0.06	
	(-0.43)	(-0.41)	
VIX	0.00	0.00	
	(0.20)	(0.23)	
Observations	608	608	
Pseudo R-squared	61.8%	61.8%	
Country FE	YES	YES	
Year FE	YES	YES	

The table presents the results of the probit model used in Eq. (4.2). The dependent variable ***GSRandNSR*** *takes the value of one from the quarter S&P assigns a GSR and an NSR simultaneously or assigns a GSR to a bank with prior NSR onwards, and zero if it is an NSR-only bank. Robust z-statistics in parenthesis. Specification (1) includes robust standard errors. Specification (2) includes robust standard errors clustered at the bank level. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. See Tables 4.3, 4.4 and 4.6 for details on the data sample. A full set of country and year dummies are included in both Specifications (1) and (2). The Marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 4.5.1.*

Table 4.10 The determinants of NSR-only assignments by S&P - Eq. (4.3)

	Dependent Variable: *OnlyNSR*		
Variable	(1)	(2)	ME(%)
Size	-0.49***	-0.49***	-17.83
	(-10.84)	(-4.67)	
Capitalratio	-0.05***	-0.05*	-2.19
	(-4.50)	(-1.77)	
Net interest	-0.01	-0.01	
	(-1.43)	(-0.58)	
NetLoanTA	-0.03***	-0.03***	-3.77
	(-8.09)	(-3.23)	
NPLratio	-0.06***	-0.06***	-0.71
	(-4.45)	(-2.70)	
Efficiency	-0.01*	-0.01	
	(-1.65)	(-0.73)	
Trading	0.00	0.00	
	(0.06)	(0.02)	
Costdebt	0.01	0.01	
	(1.34)	(1.17)	
Ownership	0.06	0.06	
	(0.42)	(0.18)	
Sovrating	0.35***	0.35***	0.83
	(9.69)	(5.66)	
VIX	0.02**	0.02***	1.09
	(2.40)	(2.92)	
Observations	1,542	1,542	
Pseudo R-squared	30.6%	30.6%	
Country FE	YES	YES	
Year FE	YES	YES	

The table presents the results of the probit model used in Eq. (4.3). The dependent variable ***OnlyNSR*** *takes the value of one from the quarter S&P assigns an NSR, onwards, and zero if the bank is not rated by S&P. Robust z-statistics in parenthesis. Specification (1) includes robust standard errors. Specification (2) includes robust standard errors clustered at the bank level. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. See Tables 4.3, 4.4 and 4.6 for details on the data sample. A full set of year dummies are included in both Specifications (1) and (2). The Marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 4.5.1.*

Table 4.11 The determinants of GSR-only assignments by S&P - Eq. (4.4)

	Dependent variable: *OnlyGSR*		
Variables	(1)	(2)	ME(%)
Size	0.39***	0.39***	17.23
	(8.10)	(2.86)	
Capitalratio	-0.03	-0.03	
	(-1.11)	(-0.91)	
Net interest	0.02***	0.02**	0.57
	(3.07)	(2.12)	
NetLoanTA	0.00	0.00	
	(0.40)	(0.22)	
NPLratio	0.02**	0.02	
	(2.49)	(1.59)	
Efficiency	-0.00	-0.00	
	(-0.60)	(-0.28)	
Trading	0.02***	0.02***	1.23
	(3.57)	(3.35)	
Costdebt	-0.01	-0.01	
	(-0.41)	(-0.34)	
Fitch	-0.51***	-0.51	-0.006
	(-2.90)	(-1.40)	
Moodys	-0.24	-0.24	
	(-1.00)	(-0.47)	
Sovrating	-0.21***	-0.21**	-7.08
	(-3.31)	(-2.14)	
VIX	0.01	0.01	
	(0.80)	(0.80)	
Observations	1,462	1,462	
Pseudo R-squared	28.4%	28.4%	
Country FE	YES	YES	
Year FE	YES	YES	

The table presents the results of the probit model used in Eq. (4.4). The dependent variable ***OnlyGSR*** *takes the value of one from the quarter S&P assigns a GSR to non-rated banks, onwards, and zero if the bank is not rated by S&P. Robust z-statistics in parenthesis. Specification (1) includes robust standard errors. Specification (2) includes robust standard errors clustered at the bank level. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. See Tables 4.3, 4.4 and 4.6 for details on the data sample. A full set of country and year dummies are included in both Specifications (1) and (2). The Marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 4.5.1.*

Table 4.12 The determinants of NSR assignments by S&P for GS-rated banks - Eq. (4.5)

Variable	Dependent variable: *NSRating*		
	(1)	(2)	ME(%)
Size	-0.40***	-0.40**	-6.82
	(-3.04)	(-2.00)	
Capitalratio	-0.04*	-0.04	
	(-1.71)	(-1.19)	
Net interest	-0.10***	-0.10	-0.47
	(-2.77)	(-1.60)	
NetLoanTA	-0.04***	-0.04**	-2.25
	(-3.69)	(-2.53)	
NPLratio	-0.03**	-0.03**	-0.21
	(-2.38)	(-1.98)	
Efficiency	-0.00	-0.00	
	(-0.57)	(-0.36)	
Trading	0.01	0.01	
	(1.48)	(0.94)	
Costdebt	-0.20***	-0.20*	-0.74
	(-3.36)	(-1.94)	
Ownership	0.40	0.40	
	(1.63)	(0.90)	
Bonding	-0.73***	-0.73*	-0.25
	(-2.81)	(-1.79)	
Fitch	-0.33**	-0.33	-0.13
	(-2.01)	(-1.03)	
Moodys	0.72**	0.72	0.25
	(2.55)	(1.45)	
Sovrating	0.00	0.00	
	(0.01)	(0.01)	
VIX	-0.01	-0.01	
	(-0.71)	(-0.70)	
Observations	468	468	
Pseudo R-squared	43.3%	43.3%	
Country FE	NO	NO	
Year FE	YES	YES	

The table presents the results of the probit model used in Eq. (4.5). The dependent variable ***NSRating*** *takes the value of one from the quarter S&P assigns an NSR to a GS-rated bank, onwards, and zero if it is a GSR-only bank. Specification (1) includes robust standard errors. Specification (2) includes robust standard errors clustered at the bank level. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. See Tables 4.3, 4.4 and 4.6 for details on the data sample. A full set of year dummies are included in both Specifications (1) and (2). The Marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 4.5.1.*

Table 4.13 The determinants of GSR assignments by S&P for NS-rated banks - Eq. (4.6)

	Dependent variable: *GSRating*		
Independent variables	(1)	(2)	ME(%)
Size	0.97***	0.97**	33.27
	(4.20)	(2.13)	
Capitalratio	0.04	0.04	
	(1.14)	(0.86)	
Net interest	-0.07	-0.07	
	(-0.61)	(-0.37)	
NetLoanTA	0.01	0.01	
	(1.19)	(0.51)	
Efficiency	0.02**	0.02	
	(1.99)	(1.04)	
Trading	0.01*	0.01	
	(1.76)	(0.96)	
Sovrating	-0.24	-0.24	
	(-0.77)	(-1.18)	
VIX	-0.01	-0.01	
	(-0.18)	(-0.17)	
Observations	186	186	
Pseudo R-squared	28.6%	28.6%	
Country FE	NO	NO	
Year FE	YES	YES	

The table presents the results of the probit model used in Eq. (4.5). The dependent variable ***GSRating*** *takes the value of one from the quarter S&P assigns a GSR to an NS-rated bank, onwards, and zero if it is an NSR-only bank. Specification (1) includes robust standard errors. Specification (2) includes robust standard errors clustered at the bank level. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. See Tables 4.3, 4.4 and 4.6 for details on the data sample. A full set of year dummies are included in both Specifications (1) and (2). The Marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 4.5.1.*

Table 4.14 The determinants of S&P rating assignments, including country-year fixed effects

	SPrating		*GSRandNSR*		*OnlyGSR*	
Variable	Eq. (4.1)	ME(%)	Eq. (4.2)	ME(%)	Eq. (4.4)	ME(%)
Size	0.22***	4.51	-0.53***	-7.58	0.64***	34.19
	(8.47)		(-5.39)		(6.60)	
Capitalratio	0.01		-0.06**	-0.83	-0.05*	
	(1.05)		(-2.49)		(-1.65)	
Net interest	0.00		0.01		0.11***	3.50
	(0.29)		(0.94)		(2.89)	
NetLoanTA	0.00		-0.01		-0.04***	-8.05
	(1.27)		(-1.31)		(-2.91)	
NPLratio	-0.00		0.01		0.01	
	(-0.41)		(0.49)		(0.44)	
Efficiency	-0.00		0.00		-0.02	
	(-1.54)		(0.52)		(-1.59)	
Trading	0.01***	0.33	0.02***	0.47	0.01	
	(4.38)		(3.76)		(0.64)	
Costdebt	-0.00		-0.07**	-0.42	-0.01	
	(-0.28)		(-2.48)			
Ownership	-0.01		0.73***	0.29		
	(-0.13)		(3.16)			
Bonding	0.15		1.19***	0.43		
	(1.34)		(3.15)			
Fitch	-0.37***	-0.11	3.25***	0.78	-1.14***	-0.004
	(-4.97)		(6.34)		(-3.92)	
Moodys	0.96***	0.31	2.83***	0.79	-1.65***	-0.01
	(12.33)		(6.95)		(-5.35)	
Sovrating	0.08		-0.47**		-1.96***	6.80
	(0.55)		(-2.12)		(-4.35)	
VIX	0.02**	0.43	0.00		0.02	
	(2.37)		(0.07)		(1.29)	
Observations	2,235		519		385	
Pseudo R-squared	28.0%		63.0%		47.0%	
Cluster by bank ID	NO		NO		NO	
Country-Year FE	YES		YES		YES	

The table reports the results of the probit models for Eqs. (4.1),(4.2) and (4.4), including a full set of ***country*year*** *interactions. Robust z-statistics in parenthesis, *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. The Marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 4.5.1.*

Table 4.15 The determinants of S&P rating assignments, considering the crisis period

	SPrating	*GSRandNSR*	*OnlyNSR*	*OnlyGSR*	*NSRating*	*GSRating*
Variable	Eq. (4.1)	Eq. (4.2)	Eq. (4.3)	Eq. (4.4)	Eq. (4.5)	Eq. (4.6)
Size	0.22***	-0.52***	-0.49***	0.43***	-0.40**	1.15**
	(2.80)	(-3.57)	(-4.67)	(2.59)	(-2.00)	(2.21)
Capitalratio	0.01	-0.04	-0.05*	-0.03	-0.04	0.05
	(0.45)	(-1.57)	(-1.77)	(-1.12)	(-1.19)	(1.19)
Net interest	0.00	0.00	-0.01	0.04**	-0.10	-0.03
	(0.05)	(0.01)	(-0.58)	(2.50)	(-1.60)	(-0.36)
NetLoanTA	0.00	-0.00	-0.03***	-0.02*	-0.04**	0.01
	(0.62)	(-0.42)	(-3.23)	(-1.68)	(-2.53)	(0.29)
NPLratio	-0.01	0.00	-0.06***	0.02	-0.03**	
	(-0.46)	(0.16)	(-2.70)	(1.16)	(-1.98)	
Efficiency	-0.00	-0.00	-0.01	-0.00	-0.00	0.03
	(-0.57)	(-0.09)	(-0.73)	(-0.28)	(-0.36)	(1.46)
Trading	0.01**	0.02*	0.00	0.00	0.01	0.01
	(2.04)	(1.89)	(0.02)	(0.76)	(0.94)	(0.98)
Costdebt	0.00	-0.03	0.01	-0.02	-0.20*	
	(0.12)	(-0.93)	(1.17)	(-0.48)	(-1.94)	
Ownership	0.16	0.60	0.06		0.40	
	(0.47)	(1.59)	(0.18)		(0.90)	
Bonding	-0.01	1.34**			-0.73*	
	(-0.04)	(2.22)			(-1.79)	
Fitch	-0.33	2.76***		-0.64	-0.33	
	(-1.54)	(3.92)		(-1.54)	(-1.03)	
Moodys	0.99***	2.73***		-0.33	0.72	
	(4.79)	(3.77)		(-0.62)	(1.45)	
Crisis	-0.84***	-1.88***	-1.19**	1.05**	-2.63***	-3.14***
	(-3.16)	(-3.58)	(-2.21)	(2.32)	(-5.55)	(-3.34)
Sovrating	-0.00	-0.06	0.35***	-0.25*	0.00	-0.76***
	(-0.03)	(-0.41)	(5.66)	(-1.82)	(0.01)	(-3.31)
VIX	0.02***	0.00	0.02***	-0.01	-0.01	0.00
	(2.58)	(0.23)	-1.19**	(-0.85)	(-0.70)	(0.02)
Observations	2,349	608	1,542	1,455	468	177
Pseudo R-squared	27.0%	62.0%	31.0%	35.0%	43.0%	34.0%
Number of clusters	321	71	241	233	41	20
Country FE	Yes	Yes	No	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the results of the probit models for Eqs. (4.1) to (4.6), including a dummy variable called 'Crisis'. ***Crisis*** *takes the value of one during the financial crisis period (January 2007 – December 2009). The model is estimated with robust standard errors. Country and year dummies are included in Eq. (4.1), (4.2) and (4.4), and only year fixed effects are used in Eq. (4.3), (4.5) and (4.6). Robust z-statistics in parenthesis, *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively.*

Table 4.16 The determinants of GSR assignments by S&P (Eq. 4.6), using NSR lagged

	Dependent variable: *GSRating (Eq. 4.6)*	
Variable	Eq. (4.6)	ME(%)
Size	0.25	
	(0.63)	
Capitalratio	0.08	
	(1.48)	
Net interest	-0.07	
	(-0.90)	
NetLoanTA	0.01	
	(0.76)	
Efficiency	0.05***	6.35
	(3.28)	
Trading	0.01	
	(0.99)	
NSRprior	0.42***	0.03
	(4.82)	
Sovrating	-0.90***	-0.07
	(-3.90)	
VIX	-0.06	
	(-0.59)	
Observations	153	
Pseudo R-squared	36.0%	
Country FE	NO	
Year FE	YES	

*The table reports the results of the probit model for Eq. (4.6), including the banks' NSR lagged four quarters (t-4) as an explanatory variable (NSRprior). The model is estimated with robust standard errors. A full set of year dummies are included. Robust z-statistics in parenthesis, *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 4.5.1.*

Table 4.17 The determinants of S&P rating assignments, using *Leverage, ROAA and NetLoandD*

	SPrating	*GSRandNSR*	*OnlyNSR*	*OlyGSR*	*NSRating*	*GSRating*
Variable	Eq. (4.1)	Eq. (4.2)	Eq. (4.3)	Eq. (4.4)	Eq. (4.5)	Eq. (4.6)
Size	0.21**	-0.53***	-0.46***	0.46***	-0.29	1.41***
	(2.56)	(-3.75)	(-3.62)	(2.62)	(-1.44)	(3.03)
(1) Leverage	0.00	-0.02	-0.05*	0.03	-0.02	0.11*
	(0.03)	(-0.94)	(-1.67)	(1.00)	(-0.46)	(1.82)
(2) ROAA	0.02	-0.03	-0.04	-0.07	-0.00	0.25
	(0.47)	(-0.57)	(-0.85)	(-1.33)	(-0.05)	(0.96)
(3) NetLoandD	-0.00	0.00	-0.01	0.00	-0.02	-0.00
	(-0.29)	(0.97)	(-1.22)	(1.31)	(-1.55)	(-0.43)
NPLratio	-0.00	0.00	-0.05**	0.01	-0.03	
	(-0.35)	(0.19)	(-2.48)	(0.86)	(-1.59)	
Efficiency	-0.00	-0.00	-0.00	0.00	-0.00	0.04*
	(-0.54)	(-0.20)	(-0.59)	(0.02)	(-0.10)	(1.84)
Trading	0.01*	0.02**	0.01	0.01	0.01	0.01
	(1.73)	(2.14)	(0.87)	(1.36)	(0.81)	(1.07)
Costdebt	0.00	-0.03	0.01	-0.02	-0.21*	
	(0.22)	(-1.07)	(1.44)	(-0.35)	(-1.78)	
Bonding	0.16	1.34**			-0.42	
	(0.47)	(2.27)			(-0.81)	
Ownership	-0.00	0.58	-0.09		0.31	
	(-0.02)	(1.49)	(-0.27)		(0.71)	
Fitch	-0.33	2.81***		-0.65	-0.14	
	(-1.57)	(3.71)		(-1.49)	(-0.44)	
Moodys	1.00***	2.77***		-0.30	0.53	
	(4.84)	(3.89)		(-0.51)	(0.97)	
Sovrat	-0.01	-0.04	0.35***	-0.20	0.03	-0.70***
	(-0.17)	(-0.26)	(5.55)	(-1.60)	(0.23)	(-2.75)
VIX	0.02***	0.00	0.02***	-0.01*	-0.01	-0.08
	(2.60)	(0.25)	(3.39)	(-1.79)	(-0.61)	(-1.12)
Observations	2,349	606	1,542	1,462	468	186
Pseudo R-squared	27.0%	62.0%	26.6%	34.0%	40.0%	33.5%
Country FE	YES	YES	NO	YES	NO	NO
Year FE	YES	YES	YES	YES	YES	YES

*The table reports the estimations of the probit model for Eqs. (4.1) to (4.6), using alternative proxies for the following financial variables: (i) Capital adequacy: Leverage; (ii) Profitability: ROAA, and (iii) Liquidity: NetLoanD. The model is estimated using standard errors clustered at the bank level. A full set of country and year dummies are included in Eq. (4.1), (4.2) and (4.4), and a full set of year dummies are included in Eq. (4.3), (4.5) and (4.6). Robust z-statistics in parenthesis, *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively.*

Table 4.18 The determinants of S&P rating assignments, considering *Leverage, ROAA and LiqAssets*

	SPrating	*GSRandNSR*	*OnlyNSR*	*OlyGSR*	*NSRating*	*GSRating*
Variables	Eq. (4.1)	Eq. (4.2)	Eq. (4.3)	Eq. (4.4)	Eq. (4.5)	Eq. (4.6)
Size	0.21**	-0.50***	-0.51***	0.49***	-0.16	1.42***
	(2.57)	(-3.48)	(-4.11)	(3.01)	(-0.94)	(3.01)
(1) Leverage	-0.00	-0.02	-0.06*	0.03	-0.03	0.11*
	(-0.02)	(-0.68)	(-1.78)	(1.01)	(-0.69)	(1.80)
(2) ROAA	0.02	-0.03	-0.05	-0.06	0.01	0.22
	(0.48)	(-0.63)	(-0.75)	(-1.18)	(0.08)	(1.19)
(3) LiqAssets	-0.00	-0.00	0.01***	0.01**	0.03***	0.00
	(-0.28)	(-0.65)	(3.18)	(2.54)	(2.65)	(0.21)
NPLratio	-0.00	0.00	-0.06***	0.02	-0.03	
	(-0.38)	(0.09)	(-2.92)	(1.00)	(-1.45)	
Efficiency	-0.00	-0.00	-0.01	-0.00	0.00	0.04**
	(-0.50)	(-0.26)	(-0.69)	(-0.19)	(0.23)	(1.98)
Trading	0.01*	0.02**	0.00	0.00	0.01	0.01
	(1.84)	(2.45)	(0.38)	(0.28)	(0.46)	(1.21)
Costdebt	0.00	-0.03	0.01	-0.01	-0.29***	
	(0.13)	(-1.06)	(1.37)	(-0.29)	(-2.80)	
Bonding	0.16	1.29**			-0.56	
	(0.47)	(2.23)			(-1.14)	
Ownership	0.00	0.52	-0.06		0.14	
	(0.02)	(1.38)	(-0.17)		(0.35)	
Fitch	-0.33	2.81***		-0.70	-0.25	
	(-1.56)	(3.61)		(-1.58)	(-0.79)	
Moodys	1.00***	2.75***		-0.31	0.45	
	(4.78)	(3.90)		(-0.54)	(0.90)	
Sovrating	-0.01	-0.04	0.40***	-0.21	-0.01	-0.64**
	(-0.13)	(-0.28)	(5.66)	(-1.64)	(-0.09)	(-2.24)
VIX	0.02***	0.01	0.02**	-0.01	-0.01	-0.09
	(2.62)	(0.36)	(2.50)	(-1.20)	(-0.83)	(-1.38)
Observations	2,349	608	1,542	1,462	468	186
Pseudo R-squared	27.0%	62.0%	31.0%	34.9%	41.5%	33.4%
Country FE	YES	YES	NO	NO	NO	NO
Year FE	YES	YES	YES	YES	YES	YES

*This table reports the estimations of the probit models for Eqs. (4.1) to (4.6), using alternative proxies for the following financial variables: (i) Capital adequacy: Leverage; (ii) Profitability: ROAA; (iii) Liquidity: LiqAssets. The model is estimated using standard errors clustered at the bank level. A full set of country and year dummies are included in Eq. (4.1), (4.2) and (4.4), and a full set of year dummies are included in Eq. (4.3), (4.5) and (4.6). Robust z-statistics in parenthesis, *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively.*

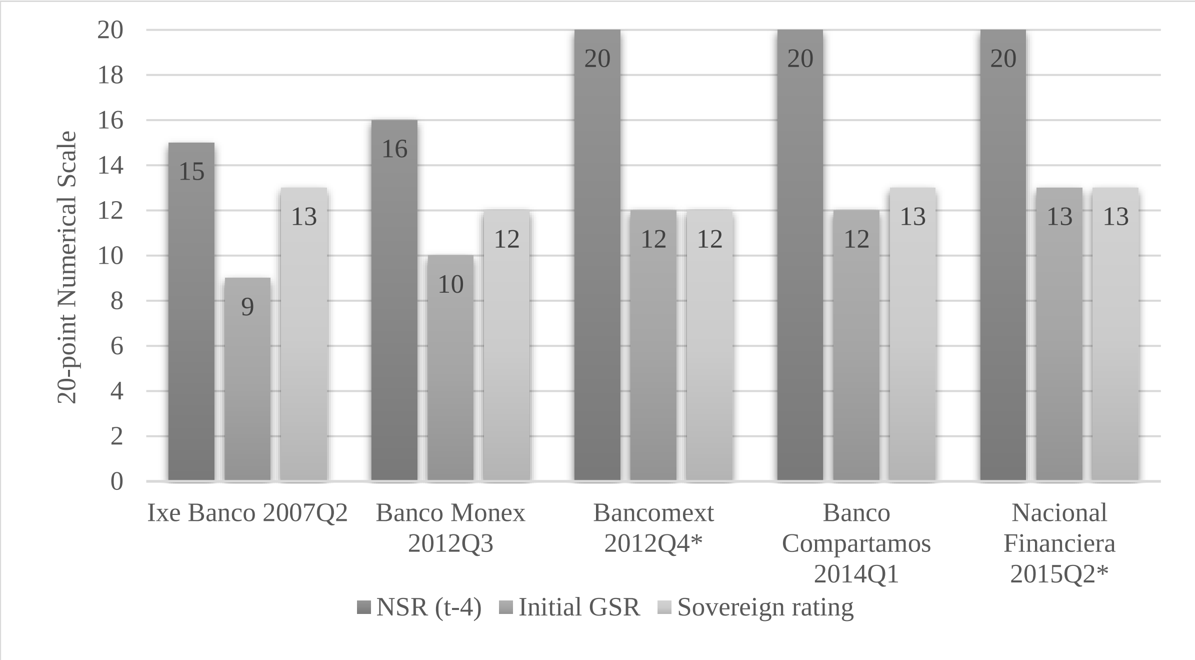
Table 4.19 The determinants of S&P rating assignments, considering *Tier1*, *ROAA and LiqAssets*

	SPrating	*GSRandNSR*	*OnlyNSR*	*OlyGSR*	*NSRating*	*GSRating*
Variable	Eq. (4.1)	Eq. (4.2)	Eq. (4.3)	Eq. (4.4)	Eq. (4.5)	Eq. (4.6)
Size	0.20***	-0.58***	-0.43***	0.45***	-0.15	1.22***
	(2.63)	(-3.70)	(-3.83)	(2.95)	(-1.02)	(2.78)
(1) Tier1	-0.01	-0.05*	-0.04	-0.02	-0.03	-0.04
	(-0.29)	(-1.69)	(-1.30)	(-0.64)	(-1.04)	(-0.65)
(2) ROAA	0.02	-0.02	-0.11*	-0.00	0.01	0.50**
	(0.54)	(-0.42)	(-1.73)	(-0.01)	(0.10)	(2.03)
(3) LiqAssets	-0.00	0.00	0.02***	0.01***	0.03***	0.00
	(-0.16)	(0.03)	(2.89)	(3.27)	(3.26)	(0.02)
NPLratio	-0.00	-0.00	-0.08***	0.03	-0.03	
	(-0.36)	(-0.01)	(-2.79)	(1.37)	(-1.48)	
Efficiency	-0.00	-0.00	-0.01	-0.00	0.00	0.03*
	(-0.51)	(-0.33)	(-0.67)	(-0.29)	(0.39)	(1.83)
Trading	0.01*	0.02**	0.00	0.00	0.01	0.01
	(1.81)	(2.51)	(0.53)	(0.20)	(0.45)	(1.24)
Costdebt	0.00	-0.04	0.01	-0.00	-0.30***	
	(0.09)	(-1.13)	(1.39)	(-0.11)	(-2.95)	
Bonding	0.16	1.35**			-0.58	
	(0.47)	(2.36)			(-1.16)	
Ownership	0.00	0.49	-0.08		0.12	
	(0.02)	(1.32)	(-0.23)		(0.30)	
Fitch	-0.33	2.79***		-0.68*	-0.27	
	(-1.57)	(3.83)		(-1.66)	(-0.86)	
Moodys	1.00***	2.74***		-0.34	0.45	
	(4.78)	(4.07)		(-0.61)	(0.94)	
Sovrating	-0.01	-0.07	0.37***	-0.23*	-0.02	-0.79***
	(-0.12)	(-0.44)	(5.43)	(-1.65)	(-0.15)	(-3.50)
vix	0.02***	0.01	0.02**	-0.01	-0.01	-0.01
	(2.63)	(0.42)	(2.29)	(-1.31)	(-0.81)	(-0.19)
Observations	2,349	608	1,542	1,462	468	186
Pseudo R-squared	27.0%	62.4%	28.9%	34.7%	41.8%	30.6%
Country FE	YES	YES	NO	NO	NO	NO
Year FE	YES	YES	YES	YES	YES	YES

*This table reports the estimations of the probit models for Eqs. (4.1) to (4.6), using alternative proxies for the following financial variables: (i) Capital adequacy: Tier1; (ii) Profitability: ROAA, and (iii) Liquidity: LiqAssets. The model is estimated using standard errors clustered at the bank level. A full set of country and year dummies are included in Eq. (4.1), (4.2) and (4.4), and a full set of year dummies are included in Eq. (4.3), (4.5) and (4.6). Robust z-statistics in parenthesis, *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively.*

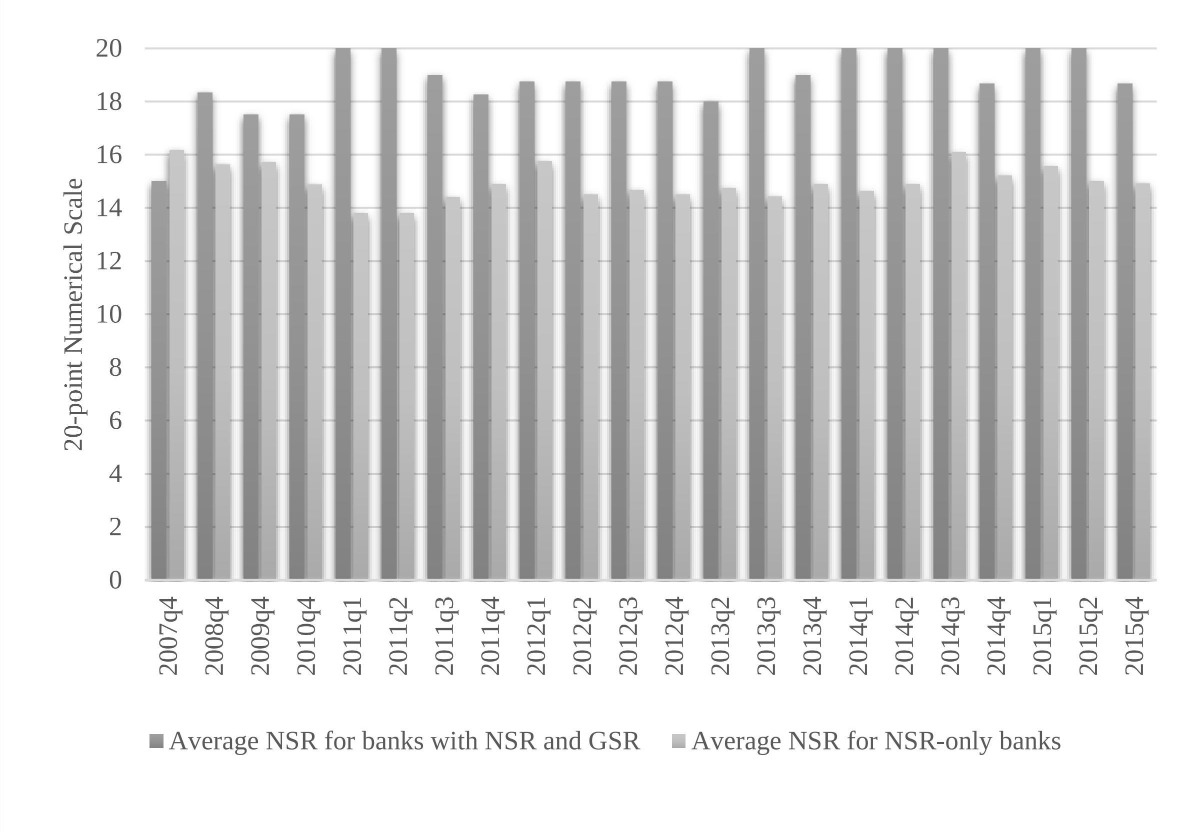
Chapter 4 Figures

Figure 4.1 Comparison of GSR and NSR assignments by S&P



*The figure presents S&P GSR assignments to NSR-rated banks during the period July 2006 to December 2015 (2006Q3-2015Q4), which corresponds to Mexican banks (see Table A 4.2). It compares each bank NSR assigned a quarter before GSR assignments, the initial assignment of GSR, and S&P's sovereign rating of Mexico during quarter where S&P assigns a GSR. The ratings are transformed into numbers based on the 20-point numerical scale. *Banks rated by Fitch and Moody's in the same year they receive a GSR by S&P.*

Figure 4.2 Comparison between average NSR and GSR - Eq. (4.6)



The figure compares the average NSR of banks with both NSR and GSR (NSR is assigned prior or at the same time as GSR) and the average NSR of NSR-only banks. The ratings are transformed to numbers based on the 20-point numerical scale.

Appendix

Table A 4.1 Dates of initial NSR and GSR assigned by S&P to the sampled banks

Bank	Country	Date (NSR)	Date (GSR)
Banco Nacional de Desenvolvimento Económico e Social	BR	27/10/10	21/10/96
Uniao de Bancos Brasileiros UNIBANCO	BR	N/A	21/05/97
Citibank NA BR	BR	07/12/99	25/11/97
Banco do Nordeste do Brazil S.A.	BR	22/06/04	10/07/98
Banco Votorantim SA	BR	06/07/01	06/07/01
Banco Indusval SA	BR	04/01/05	04/01/05
Banco BMG SA	BR	03/05/05	03/05/05
Banco Mercantil do Brasil S.A.	BR	04/10/05	04/10/05
Banco Fibra S.A.	BR	24/11/05	24/11/05
Banco Safra	BR	16/02/11	12/01/06
Banco Pan S.A.	BR	01/02/06	01/02/06
Banco Daycoval SA	BR	10/05/06	10/05/06
Banco Pine SA	BR	09/06/06	26/05/06
Banco Itau BBA S.A.	BR	25/04/03	09/06/06
Banco Santander (Brasil) S.A.	BR	06/09/06	06/09/06
BES Investimento do Brasil SA- Banco de Investimento	BR	19/01/10	19/01/10
Banco do Estado do Rio Grande do Sul S.A. BANRISUL	BR	05/03/12	05/03/12
Banco BTG Pactual SA	BR	03/04/12	03/04/12
Banco de Desenvolvimento de Minas Gerais SA - BDMG	BR	23/11/12	23/11/12
Caixa Economica Federal	BR	25/09/13	25/09/13
Banco do Estado do Para SA - BANPARA	BR	24/10/13	24/10/13
Itau Unibanco SA	BR	29/06/15	29/06/15
Banco Intermedium SA	BR	19/02/10	N/A
Banco Toyota do Brasil S.A.	BR	27/06/08	N/A
Bank of China Limited	CN	28/04/11	15/02/94
Industrial & Commercial Bank of China (The) - ICBC	CN	28/04/11	09/11/94
Bank of Communications Co. Ltd	CN	28/04/11	10/11/94
China Construction Bank Corporation Joint Stock Company	CN	28/04/11	10/06/98
China Merchants Bank Co Ltd	CN	28/04/11	22/10/07
Bank of Nanjing	CN	09/08/11	09/08/11
Agricultural Bank of China Limited	CN	16/12/12	16/12/12
Shanghai Pudong Development Bank	CN	24/06/13	24/06/13
Shanghai Rural Commercial Bank	CN	04/11/14	04/11/14
China Minsheng Banking Corporation	CN	17/02/15	17/02/15
Banco Davivienda	CO	N/A	28/10/11
Banco de Bogota SA	CO	N/A	08/12/11
Bancolombia S.A.	CO	N/A	26/11/12
Bank Negara Indonesia (Persero) - Bank BNI	ID	22/11/12	26/08/96
PT Bank CIMB Niaga Tbk	ID	N/A	16/01/97
Bank Mandiri (Persero) Tbk	ID	22/11/12	30/11/01
Bank Danamon Indonesia Tbk	ID	22/11/12	18/09/02
Indonesia Eximbank	ID	03/05/11	03/05/11
Bank Rakyat Indonesia (Persero) Tbk	ID	02/05/12	02/05/12
Kazkommertsbank Joint-Stock Company	KZ	23/10/12	07/10/97
OJSC Halyk Savings Bank of Kazakhstan	KZ	16/07/14	10/10/97
AsiaCredit Bank JSC	KZ	10/10/11	30/06/00
Nurbank JSC	KZ	24/01/11	22/01/02
CJSC Development Bank of Kazakhstan	KZ	23/08/12	23/07/02
TsesnaBank JSC	KZ	29/12/09	15/08/05
Agrarian Credit Corporation	KZ	18/10/06	18/10/06
Eurasian Bank	KZ	09/11/06	09/11/06
JSC Kazinvestbank	KZ	04/12/06	04/12/06

(Continued on next page)

Table A 4.1 (continued)

Bank	Country	Date (NSR)	Date (GSR)
ForteBank JSC	KZ	10/06/10	10/10/07
ATFBank JSC	KZ	N/A	12/12/08
Delta Bank	KZ	27/06/11	27/06/11
Bank CenterCredit	KZ	29/12/11	29/12/11
Bank RBK JSC	KZ	30/01/12	30/01/12
Kaspi Bank AO	KZ	05/12/12	05/12/12
Subsidiary JSC Bank VTB (Kazakhstan)	KZ	27/09/13	27/09/13
JSC Capital Bank Kazakhstan	KZ	12/02/14	12/02/14
Export-Import Bank of the Republic of Kazakhstan (Eximbank AO)	KZ	08/04/15	08/04/15
Banco Nacional de Mexico, SA - BANAMEX	MX	31/12/98	27/04/93
BBVA Bancomer S.A.	MX	17/01/05	17/12/96
Banco Inbursa SA	MX	09/04/03	14/11/97
Banco Mercantil del Norte S.A. - BANORTE	MX	31/08/12	04/06/99
Scotiabank Inverlat SA	MX	26/03/04	26/03/04
HSBC Mexico, SA	MX	31/12/98	21/06/04
Banco Santander (Mexico) SA	MX	17/02/05	31/01/05
Banco Nacional de Obras y Servicios Publicos, SNC - BANOBRAS	MX	11/10/06	11/10/06
Ixe Banco SA	MX	14/02/06	11/02/07
Banca Mifel, SA de CV	MX	06/06/07	06/06/07
Banco Ahorro Famsa SA	MX	25/05/11	25/05/11
Banco Monex SA	MX	21/08/06	17/05/12
Banco Nacional de Comercio Exterior SNC - BANCOMEXT	MX	01/03/02	03/09/12
Consubanco, S.A. Institucion de Banca Multiple	MX	20/11/12	20/11/12
Banco Compartamos SA de CV-CompartamosBanco	MX	06/12/11	10/10/13
Nacional Financiera S.N.C.	MX	27/09/04	23/02/15
Afirme Grupo Financiero SA	MX	10/10/03	N/A
American Express Bank (Mexico) SA	MX	14/03/07	N/A
Arrendadora Afirme, S.A. de C.V.	MX	10/10/03	N/A
Banca Afirme	MX	06/07/99	N/A
Banco del Ahorro Nacional y Servicios Financieros SNC-BANSEFI	MX	07/08/14	N/A
Banco Inmobiliario Mexicano SA	MX	12/11/09	N/A
Banco Invex SA	MX	04/07/02	N/A
Banco Multiva SA	MX	23/08/12	N/A
Banco Regional de Monterrey S.A. - BANREGIO	MX	01/11/06	N/A
Banco Ve por Mas, SA	MX	12/04/07	N/A
Bank of America (Mexico)	MX	11/12/03	N/A
Bansi, S.A., Institución de Banca Múltiple	MX	23/04/01	N/A
CIBanco SA, Institucion de Banca Multiple	MX	19/10/01	N/A
Factoraje Afirme, S.A. de C.V	MX	13/10/03	N/A
Holding Monex S.A.B de CV	MX	17/05/12	N/A
Inter Banco SA Institución de Banca Múltiple	MX	23/06/11	N/A
Investa Bank SA	MX	08/11/04	N/A
Ixe Grupo Financiero SA	MX	14/02/06	N/A
Sociedad Hipotecaria Federal SNC	MX	04/10/02	N/A
Guaranty Trust Bank Plc	NG	26/03/09	27/11/06
Zenith Bank Plc	NG	26/03/09	16/11/07
First City Monument Bank Ltd	NG	28/05/09	22/05/08
Access Bank Plc	NG	12/03/09	12/03/09
First Bank of Nigeria Ltd	NG	11/06/13	11/06/13
Skye Bank Plc	NG	07/08/13	07/08/13
Stanbic IBTC Bank Plc	NG	13/11/13	13/11/13
Alfa-Bank OJSC	RU	17/12/03	27/01/99
Bank Petrocommerce	RU	18/10/02	04/08/00
Public Joint Stock Company "Bank UralSib'	RU	N/A	31/08/01
UniCredit Bank AO	RU	N/A	31/01/02

(Continued on next page)

Table A 4.1 (continued)

Bank	Country	Date (NSR)	Date (GSR)
TransCreditBank Group OAO-TransCreditBank	RU	04/06/07	03/06/02
Russian Standard Bank Group-Russian Standard Bank JSC	RU	22/07/02	02/06/03
Bank SOYUZ	RU	24/09/03	24/09/03
Gazprombank Open Joint-Stock Company	RU	02/12/03	02/12/03
Ural Bank for Reconstruction & Development	RU	09/11/05	04/03/04
VTB Bank (public joint-stock company)-JSC VTB Bank	RU	14/06/06	27/04/04
Public joint-stock company ROSBANK	RU	28/04/04	28/04/04
OJSC Promsvyazbank	RU	22/07/13	13/07/04
Home Credit and Finance Bank	RU	N/A	20/12/04
Vnesheconombank	RU	N/A	28/06/05
Bank VTB24 CJSC	RU	24/08/06	24/08/06
JSC Krayinvestbank	RU	10/05/07	10/05/07
West Siberian Commercial Bank-Zapsibcombank	RU	16/07/07	16/07/07
AO Raiffeisenbank	RU	25/09/07	25/09/07
B&N Bank Joint Stock Company	RU	29/10/04	10/08/09
Globexbank-Commercial Bank Globex	RU	29/09/09	29/09/09
Sovkombank LLC	RU	29/10/10	29/10/10
OTKRITIE Bank JSC	RU	19/07/11	19/07/11
Sviaz-Bank OAO	RU	12/10/11	12/10/11
Credit Bank of Moscow	RU	27/01/12	27/01/12
Nota-Bank Open Joint-Stock Company	RU	13/06/13	13/06/13
PJSC Tatfondbank	RU	24/03/14	24/03/14
PJoint-Stock Company 'Bank Otkritie Financial Corporation'	RU	04/04/14	04/04/14
The joint-stock Bank 'ROSEVROBANK'	RU	28/09/15	28/09/15
Kasikornbank Public Company Limited	TH	14/07/09	22/02/95
Bangkok Bank Public Company Limited	TH	21/05/09	06/03/95
Siam Commercial Bank Public Company Limited	TH	21/05/09	13/11/95
Bank of Ayudhya Public Company Ltd.	TH	31/07/09	26/08/96
United Overseas Bank (Thai) PCL	TH	14/10/10	04/11/96
Krung Thai Bank Public Company Limited	TH	22/11/12	18/09/03
TMB Bank Public Company Limited	TH	21/05/09	14/02/06
FirstRand Limited	ZA	14/04/11	14/04/11
Standard Bank of South Africa Ltd.	ZA	N/A	15/07/11
Nedbank Limited	ZA	10/12/12	10/12/12
Investec Bank Limited	ZA	19/02/14	19/02/14
FirstRand Bank Ltd	ZA	14/04/11	29/10/14

The table presents the list of sampled banks, including the dates of their initial NSR and/or GSR assignments by S&P. 'N/A' stands for not applicable. Data is available from Capital IQ. BR: Brazil; CN: China; CO: Colombia; ID: Indonesia; KZ: Kazakhstan; MX: Mexico; NG: Nigeria; RU: Russian Federation (The); TH: Thailand, ZA: South Africa.

Table A 4.2 Banks with initial national and/or global ratings assigned by S&P

Country	GSR assignments to NSR-rated banks	Banks GSR-only	Banks with NSR and GSR assigned on the same day	Banks NSR-only	NSR assignments to GSR-rated banks	NSR and GSR assignments before the period of analysis
	I	*II*	*III*	*IV*	*V*	*VI*
BR	0	0	10	2	2	11
CN	0	0	5	0	5	0
CO	0	3	0	0	0	0
ID	0	0	2	0	3	1
KZ	0	1	10	0	7	0
MX	5	0	4	8	1	17
NG	0	0	4	0	3	0
RU	0	0	14	0	3	12
TH	0	0	0	0	7	0
ZA	0	1	3	0	1	0
Total	**5**	**5**	**52**	**10**	**32**	**41**

The table presents the number of banks with initial NSRs and/or GSRs assigned by S&P during the period July 2006 to December 2015 (period of analysis), after the matching process with the financial data. Column (I) presents the number of banks with initial GSR assigned in the period of analysis, which are NS-rated (with NSR assigned prior to the period of analysis). Column (II) shows the number of banks with only GSR assigned in the period of analysis. Column (III) registers the number of banks with both NSR and GSR assigned for the first time on the same quarter during the period of analysis. Column (IV) presents the banks with only an NSR assigned for the first time during the period of analysis. Column (V) presents the number of banks with NSR assigned for the first time during the period of analysis, which are GS-rated (have a GSR assigned prior to the period of analysis).Column (VI) presents the number of banks with initial NSR and GSR assigned before the period of analysis.

Table A 4.3 Literature on proxies of Capital, Profitability and Liquidity

Financial variable	*Ratio*	*Type of research*	*Research that includes the variable*
Capital	Tier 1	Bank risk	Leung et al. (2015)
		Credit ratings	Karminsky and Khromova (2016)
	Capital adequacy ratio	Bank risk	Anginer et al. (2018)
		Credit ratings	Huang and Shen (2015)
		Credit ratings	Bissoondoyal-Bheenick and Treepongkaruna (2011)
	Ratio of equity to total assets	Credit ratings	Shen et al. (2012)
		Credit ratings	Salvador et al. (2018)
		Credit ratings	Hau et al. (2013), inverse ratio
Profitability	ROA	Credit ratings	Salvador et al. (2018)
		Credit ratings	Hau et al. (2013)
		Credit ratings	Karminsky and Khromova (2016)
	Ratio of net interest income to average earning assets	Credit ratings	Shen et al. (2012)
		Bank risk	Ashraf (2018)
	Ratio of non-interest income to gross revenues	Credit ratings	Hau et al. (2013)
		Bank risk	Baele et al. (2007)
		Bank risk	Ashraf (2018)
		Credit ratings	Klusak et al. (2017)
Liquidity	Ratio of loans to total assets	Credit ratings	Morgan (2002)
		Credit ratings	Iannotta (2006)
		Credit ratings	Poon et al. (2009)
		Credit ratings	Hau et al. (2013)
		Bank risk	Weiß et al. (2014)
		Bank risk	De Jonghe et al. (2015)
		Bank risk	Leung et al. (2015)
		Bank risk	Arena (2008)
		Bank risk	Vazquez and Federico (2015)
	Ratio of net loans to deposits and short-term funding	Credit ratings	Poon et al. (2009)
		Credit ratings	Bissoondoyal-Bheenick and Treepongkaruna (2011)
	Ratio of liquid assets to deposits and short-term funding	Credit ratings	Shen et al. (2012)
		Credit ratings	Poon et al. (2009)
		Credit ratings	Karminsky and Khromova (2016)

The table reports a summary of the studies investigating credit ratings or bank risk and the financial variables used as proxies of capital, profitability and liquidity.

Table A 4.4 Correlation matrix of the financial variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Total Assets (1)	1											
Leverage (2)	-0.21	1										
ROAA (3)	-0.01	0.31	1									
Tier 1 (4)	-0.17	0.76	0.22	1								
Capitalratio (5)	-0.17	0.72	0.21	0.94	1							
NetLoanTA (6)	-0.08	0.13	0.01	-0.14	-0.11	1						
NetLoanD (7)	-0.11	0.41	0.12	0.17	0.16	0.50	1					
LiqAssets (8)	-0.10	0.12	0.07	0.31	0.29	-0.62	0.00	1				
NPLratio (9)	-0.12	0.17	-0.18	0.09	0.12	-0.02	0.11	0.02	1			
Netinterest (10)	-0.13	0.34	0.27	0.21	0.18	0.08	0.20	-0.02	0.31	1		
Efficiency (11)	-0.23	0.05	-0.40	0.08	0.07	-0.12	-0.08	0.10	0.14	0.09	1	
Trading (12)	-0.01	-0.09	0.07	-0.07	-0.04	-0.23	-0.15	0.20	-0.05	-0.27	0.05	1

The table presents the correlation matrix of the financial variables used in the estimations and robustness tests.

Table A 4.5 Number of observations with NSR and GSR in the matched sample

***Panel A**. Number of NSR and GSR ratings per region in the matched sample*

Year	Latin America[a]		Asia		Europe		Africa	
	NSR	GSR	NSR	GSR	NSR	GSR	NSR	GSR
2006	17	21	0	0	4	13	0	0
2007	39	41	0	0	12	23	0	0
2008	50	47	0	15	11	22	0	2
2009	50	46	8	44	18	29	2	3
2010	56	51	18	35	15	22	3	5
2011	91	67	29	46	16	26	5	7
2012	118	84	38	47	32	36	10	12
2013	91	64	43	42	40	40	11	13
2014	128	86	44	44	49	50	12	13
2015	95	71	38	38	33	33	6	11
TOTAL	735	578	218	311	230	294	49	66

***Panel B.** Number of NSR and GSR ratings per country in the matched sample*

Year	Brazil		China		Colombia		Indonesia		Kazakhstan		Mexico		Nigeria		Russia		Thailand		South Africa	
	NSR	GSR	NSR	GSR	NSR	GSR	NSR	GSR	NSR	GSR	NSR	GSR	NSR	GSR	NSR	GSR	NSR	GSR	NSR	GSR
2006	11	14	0	0	0	0	0	0	0	5	6	7	0	0	4	8	0	0	0	0
2007	26	32	0	0	0	0	0	0	1	7	13	9	0	0	11	16	0	0	0	0
2008	32	37	0	5	0	0	0	3	1	6	18	10	0	1	10	16	0	7	0	1
2009	32	37	0	16	0	0	0	2	2	6	18	9	2	2	16	23	8	26	0	1
2010	37	40	0	14	0	0	0	3	2	5	19	11	3	3	13	17	18	18	0	2
2011	41	37	8	14	0	0	1	8	4	9	50	30	4	4	12	17	20	24	1	3
2012	46	41	15	15	0	0	2	7	8	10	72	43	9	9	24	26	21	25	1	3
2013	34	32	17	17	0	0	9	8	13	11	57	32	7	7	27	29	17	17	4	6
2014	52	49	17	17	0	2	8	8	13	13	76	35	8	8	36	37	19	19	4	5
2015	37	35	14	14	0	5	11	11	10	10	58	31	1	5	23	23	13	13	5	6
Total	348	354	71	112	0	7	31	50	54	82	387	217	34	39	176	212	116	149	15	27

The table reports the number of observations from the sample with NSR and/or GSR assignments by S&P, per region (Panel A) and per country (Panel B) for each year between 2006 and 2015. ***a.*** *In the sample of banks with ratings assigned by S&P, Latin America corresponds to banks located in Brazil, Colombia and Mexico.*

Table A 4.6 Correlation matrix of the quarterly NSR and GSR observations per country

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
NSR BR (1)	1																		
GSR BR (2)	0.96	1																	
NSR CN (3)	0.67	0.49	1																
GSR CN (4)	0.72	0.60	0.71	1															
GSR CO (5)	0.41	0.34	0.47	0.36	1														
NSR ID (6)	0.53	0.40	0.78	0.55	0.69	1													
GSR ID (7)	0.71	0.56	0.73	0.71	0.53	0.76	1												
NSR KZ (8)	0.65	0.54	0.71	0.62	0.62	0.69	0.74	1											
GSR KZ (9)	0.66	0.59	0.54	0.52	0.53	0.51	0.69	0.93	1										
NSR MX (10)	0.77	0.62	0.76	0.68	0.35	0.64	0.82	0.57	0.51	1									
GSR MX (11)	0.75	0.62	0.72	0.61	0.26	0.55	0.75	0.50	0.47	0.97	1								
NSR NG (12)	0.65	0.51	0.64	0.60	0.17	0.44	0.66	0.78	0.78	0.58	0.55	1							
GSR NG (13)	0.72	0.58	0.73	0.70	0.44	0.56	0.76	0.91	0.90	0.65	0.59	0.93	1						
NSR RU (14)	0.80	0.72	0.70	0.73	0.41	0.60	0.79	0.78	0.81	0.82	0.77	0.79	0.86	1					
GSR RU (15)	0.77	0.73	0.56	0.67	0.31	0.47	0.72	0.72	0.80	0.76	0.73	0.76	0.81	0.98	1				
NSR TH (16)	0.72	0.55	0.72	0.77	0.30	0.52	0.65	0.58	0.45	0.69	0.64	0.63	0.66	0.57	0.48	1			
GSR TH (17)	0.63	0.51	0.49	0.86	0.18	0.30	0.59	0.44	0.38	0.59	0.55	0.51	0.56	0.55	0.52	0.74	1		
NSR ZA (18)	0.57	0.45	0.72	0.57	0.74	0.82	0.71	0.90	0.80	0.48	0.40	0.65	0.79	0.67	0.57	0.52	0.35	1	
GSR ZA (19)	0.64	0.51	0.72	0.67	0.62	0.73	0.80	0.95	0.90	0.56	0.49	0.76	0.89	0.78	0.71	0.60	0.49	0.93	1

The table reports the correlation matrix of the observations from the matched sample (see Table 4.2) with NSR or GSR assignments by S&P per country during the period of July 2006 to December 2015.

Chapter 5 Split bank ratings and information opacity in emerging economies

BANGOR UNIVERSITY

5.1 Introduction

Credit rating agencies (CRAs) provide independent opinions about the creditworthiness of an issuer (or issue). When more than one CRA assigns a rating to an issuer (or issue) at the same time, any differences in their credit opinion are termed as 'split ratings'. The literature on split ratings is mainly focused on S&P, Moody's and Fitch, the global rating agencies (GRAs), because of their significant market share in terms of number of ratings (See Section 2.1) and because GRAs' rating disagreements provide a measure of the issuer's degree of opacity (Morgan, 2002; Iannotta, 2006; Livingston et al., 2007). As a result, investors demand a higher yield premium for bonds with split ratings by GRAs as compensation for the issuer's opacity problems (Livingston and Zhou, 2010). Moreover, if one GRA tends to assign lower ratings than the other GRA when split ratings occur, research suggests that investors incorporate the behaviour of the most conservative GRA to the yield premium required for split-rated bonds (Livingston et al., 2010). This Chapter aims to examine the factors that determine GRAs' split ratings and if there is a tendency to assign bank ratings in a more conservative manner in emerging economies. The Chapter also investigates the influence of split bank ratings on future bank rating changes.

The causes of split ratings between GRAs have been broadly researched, testing two main hypotheses: the random error proposed by Ederington (1986), and the opacity hypothesis by Morgan (2002). The literature shows evidence that rather than random errors, split ratings are driven by asset opacity of the rated firms. As proxies of opacity, previous studies use financial and accounting variables (e.g. Morgan, 2002; Bowe and Larik, 2014) and analyst earnings forecasts (e.g. Livingston et al., 2007; Livingston and Zhou, 2010, 2016), finding mixed results on their impact on split ratings (see Section 3.2.4 and 5.2.1). Previous research on the causes of split ratings, however, is mainly focused on corporates from the US and Europe. In contrast, the causes of split ratings in emerging economies have been barely explored and are mainly focused on sovereign ratings (Alsakka and ap Gwilym, 2010c, 2012) and Chinese non-financial firms (Jiang and Packer, 2019).

The banking industry has the highest level of opacity among all sectors (Morgan, 2002; Flannery et al., 2004, 2013). Opacity can influence a bank's funding cost and increase the bank's risk-taking behaviour, which has a strong negative effect on bank stability (Fosu et al., 2017). Higher asset opacity also prevents banks from accurately pricing equity risk (Leung et al., 2015). Since there is a strong interconnection between banks and other industries, a less stable banking industry can have pervasive effects on the overall economy. The effects of bank opacity in emerging economies are much more relevant, as the relatively low transparency and weak institutional environment restrict borrowers' opportunities to seek funding through the capital markets. Thus, the use of bank loans is proportionally more common than in developed economies (Nagano, 2018). As the literature shows that split ratings are a good proxy of opacity, the investigation on the proportion and magnitude of the split ratings in the banking sector of emerging economies, and the drivers of those disagreements can shed light on the bank opacity characteristics in these economies. Examining split bank ratings can also shed light on the effectiveness of market discipline and the risk-taking behaviour of the banks in emerging economies, aspects that are highly relevant for policy makers and other market participants. Accordingly, the first research question of this Chapter is: 'does bank opacity influence GRAs' split ratings of banks in emerging countries?'.

The second research question examines the link between the bank rating disagreements and future bank rating changes in emerging economies, considering the effect of the magnitude of the split ratings. Previous research on split ratings between GRAs has revealed that GRAs disagreements have a significant impact on the probability of rating migrations (Livingston et al., 2008; Alsakka and ap Gwilym, 2009, 2010c). Furthermore, it is reported that harsher split ratings are related to firms or sovereigns with higher information asymmetries, hence there is a strong link between opacity and rating migration (Alsakka and ap Gwilym, 2010c, 2010b). This link is also explored for bank ratings in emerging markets in this Chapter.

To answer the research questions, the Chapter employs a panel dataset of 862 observations (78 banks) with global ratings assigned by S&P and Moody's from 9 emerging economies; 798 observations (76 banks) with global ratings assigned by S&P and Fitch from 10 emerging economies; and 813 observations (64 banks) with global ratings assigned by Moody's and Fitch (813) from 9 emerging countries, for the period from 2008 to 2015. Prior studies on split bank and corporate ratings are focused on rating disagreements between S&P and Moody's (Morgan, 2002; Iannotta, 2006; Livingston et al., 2007, 2010). Although the increasing market share of Fitch has motivated the analysis of split corporate ratings including Fitch's ratings as a third GRA (Bongaerts et al., 2012; Livingston and Zhou, 2016), there are no studies on bank ratings disagreements including all three GRAs. This Chapter addresses the void in the literature, examining split bank ratings of each pair of the three GRAs. As preliminary evidence of the relevance of studying split bank ratings in emerging economies, the descriptive analysis shows that, on average, more than 66% of the observations have split bank ratings between GRAs

(See Section 5.4.1). This is substantially higher compared to earlier studies. For instance, Iannotta (2006) reported a figure of 36.7% for split-rated bonds from a sample of European banks, while Livingston and Zhou (2016) identified 47.7% of split-rated bonds from a sample of European corporates.

The results show that opacity has a significant effect on split bank ratings. Bank *Size, Liquidity* and *Profitability* are the most relevant financial variables that affect split bank ratings and the investigation of banks rated by all three GRAs shows that split ratings are strongly affected by the bank's liquidity. Moreover, previous research shows that split ratings are lopsided, with one GRA assigning more conservative ratings (lower ratings) than the other GRA, especially when the asset opacity is high (e.g. Morgan, 2002; Livingston et al., 2010). The results in this Chapter confirm the tendency of S&P to be more conservative when assigning bank ratings, as S&P assigns lower ratings in 80% of the split ratings observations against Moody's and Fitch. Between Moody's and Fitch, the latter GRA is more conservative. The findings of this Chapter also show that split-rated banks are more likely to experience future rating changes than non-split rated banks. Moreover, the marginal effects reveal that higher rating differences in notches have a stronger effect on future rating migrations. When analysing the dynamic between GRAs, the results show a strong interdependency between S&P and Fitch ratings, while Moody's inferior or superior rating assignments have the weakest effect on future rating changes by S&P or Fitch.

The remainder of the Chapter is organised as follows. Section 5.2 provides the literature review on split bank ratings and rating migrations. Section 5.3 presents the hypotheses and research questions. Section 5.4 describes the data sample and the variables used in the estimations. Section 5.5 presents the methodology, Section 5.6 discusses the empirical results and presents the robustness tests. Finally, Section 5.7 concludes the Chapter.

5.2 Literature review

Published research on rating disagreements has focused on GRAs, because of the oligopolistic characteristics of the credit rating industry (see Section 2.1). Furthermore, the overreliance on GRAs' rating changes has drawn the attention of academia on the certification effect of their ratings (See Section 3.2.1), while the competition between them has questioned the rating practices and its effect on rating quality (see Section 3.2.2). The prior literature addresses the causes of split ratings within a framework of two dominant hypotheses: the random error hypothesis and the opacity hypothesis (see Section 3.2.4). Ederington (1986) examines the random error hypothesis, using a sample of the US corporate bond ratings assigned by S&P and Moody's, and argues that differences in the assigned ratings to the same corporates are explained by unsystematic or random differences in GRA's opinion rather than by dissimilarities in rating methodologies. Ederington (1986) shows that differences in ratings often occur in borderline rating categories, where the probability of error on the assessment of the issuer's creditworthiness is higher.

The random error hypothesis is tested by Cantor and Packer (1997) for the US corporations rated by four CRAs: Moody's, S&P, Fitch and Duff & Phelps Credit Rating Agency.[96] They find that split ratings do not occur randomly; instead, the disagreements are an outcome of differences in the rating criteria and rating scales. Morgan (2002) studies the causes of split ratings between S&P and Moody's for the US banking industry. He finds that among all economic sectors, the highest uncertainty measured by rating disagreements (split ratings) between S&P and Moody's occurs in the US banking industry, arguing that banks are more opaque than non-financial institutions. Furthermore, Morgan (2002) shows that bank size, trading assets and a higher percentage of securities compared to loans have a significant impact on split bank ratings, thereby, providing evidence of the important role of asset opacity in rating disagreements. The opacity hypothesis proposed by Morgan (2002) is corroborated by Iannotta (2006) for European banking and non-banking firms. He shows that opacity occurs more often in the banking sector than in other industries. Smaller size, a higher share of portfolio investment activities (compared to lending) and a weaker capital are the main variables that increase uncertainty, hence, the split ratings between S&P and Moody's.

[96] In March 2000 Fitch Ratings acquired Duff & Phelps Credit Rating Agency (DCR).

Livingston et al. (2007) examine both the random error hypothesis[97] and the opacity hypothesis for a sample of US corporate ratings. The study argues that split-rated corporates maintain the rating disagreements in the long term, hence, split ratings are not entirely associated with the random element proposed by Ederington (1986). They corroborate the opacity hypothesis by Morgan (2002), showing that split corporate ratings incorporate an element of uncertainty associated with the lack of transparency and opacity in the information provided by the firms. For emerging economies, Ismail et al. (2015) find that asymmetric information measured by the debt-to-equity ratio is a strong driver of split corporate ratings in emerging markets. For sovereign ratings, Vu et al. (2017) examine sovereign split ratings in European and non-European countries, finding that a lack of government transparency and higher political risk increase the probability of having sovereign split ratings. This suggests that split sovereign ratings arise more frequently in economies characterised by opacity (see Section 3.2.4).

The literature on split ratings presents different empirical measures of asset opacity. Morgan (2002) tests the effects of asset opacity on split bond ratings from S&P and Moody's for bonds issued by US banks. The financial ratios used as proxies of information opacity are: total assets, cash, total loans, trading assets, and the capital to asset ratio. Iannotta (2006) tests the opacity theory using the following financial ratios: total assets, loans, earning assets (alternatively also non-earning assets), fixed assets, liquid assets and equity to total assets ratio. A second approach to asset opacity is presented by Livingston et al. (2007). They use an asset opacity index (OI), constructed using the average weight of the following variables: financial ratios (firm size, market to book ratio and intangible assets), the standard deviation of analysts' earnings forecasts, the number of stock analysts, the bid-ask spread as a percentage of the stock price issued by the firm (called adverse selection), and the bond maturity. They find that all variables are significant except for the adverse selection proxy. From a different perspective, Livingston and Zhou (2016) examine the influence of a third rating agency (Fitch Ratings), on the information-opacity premiums on corporate bonds with split ratings from S&P and Moody's. They use the index OI as an explanatory variable, however, they limit OI to four opacity proxies to avoid noise in their estimations: firm size, standard deviation of analyst forecasts, analyst forecast errors, and stock return volatility (measured as the standard deviation of the daily stock returns 250 days before the bond issue).

[97] The hypothesis presented by Ederington (1986) was named "the random error hypothesis of split ratings" by Livingston et al. (2007).

Regarding the effect of opacity on bond yields, Livingston and Zhou (2010) show that split-rated bonds yields are 7 percentage points higher than non-split bonds, suggesting that split ratings are a good proxy of opacity. Livingston and Zhou (2016) find that the opacity index (OI) has a positive impact on bond spreads. Moreover, they find that the third rating (Fitch) is perceived as additional information, reducing the opacity and thereby, decreasing the requested opacity premiums. The measures of opacity are used by Dahiya et al. (2017), who find that the best measures are the number of analysts that follows a firm and the Amihud's (2002) illiquidity measure.[98]

An additional strand of credit rating literature suggests that split ratings have a significant effect on future rating migrations. Livingston et al. (2008) examine bond ratings assigned by Moody's and S&P in the US corporate industry[99] and find that split-rated bonds are more likely to experience rating changes than non-split bonds. Moreover, the GRA that assigns the lower rating at the initial issuance, is more likely to upgrade the bond in the next years. In a study of the Korean rating industry, Park and Lee (2018) analyse the ratings assigned to unsecured bond issues by the national rating agencies (NRAs): Korea Ratings, NICE and Korea Investors Service. They find that if issuers hire a third NRA, and that NRA assigns a rating lower than the other two NRAs, the likelihood of future rating upgrades by the other two NRAs increases. For sovereigns in emerging economies, previous studies find that split sovereign ratings increase the probability of future sovereign rating changes. Specifically, sovereigns with split ratings have a higher probability of being upgraded (downgraded) by the CRA that assigned the lower (higher) rating after a year (see Alsakka and ap Gwilym, 2010c). Alsakka et al. (2017) examine sovereign split ratings between GRAs in European countries and find that S&P inferior ratings influence future rating downgrades by Fitch and Moody's, while Moody's lower ratings influence Fitch negative future actions. For structured finance ratings, Lugo et al. (2015) find that split ratings ultimately lead to rating convergence, although the convergence is associated with the GRA's market reputation (See Section 3.2.4).

To summarize, two aspects stand out from the literature review relevant to this thesis. Firstly, previous studies show that opacity is the main cause of split ratings, however, the research is focused mainly on sovereigns, banks and corporates from developed economies. Secondly, split ratings have a strong influence on future rating changes, and the magnitude of the split (in

98 Amihud (2002) measures illiquidity as the average (over the fiscal year) of the ratio between the absolute daily return and the daily dollar volume.

99 Livingston et al. (2008) incorporates bond rating data of companies from the US financial, industrial and utility sectors.

notches) significantly influences the magnitude of the future rating changes, reflecting the effect of opacity. The emphasis in these economies is most likely related to higher information quality and the significant number of companies rated by the GRAs. Nevertheless, these aspects do not diminish the relevance of investigating split bank ratings in emerging economies. Indeed, examining the drivers of split bank ratings and the effect of bank splits on future bank rating changes is even more relevant, considering the opacity features of the banking industry and the government in these economies, and the void in the literature examining these aspects.

5.3 Hypotheses and research questions

The purpose of this Chapter is to investigate the reasons for split bank ratings in emerging markets. Split ratings can be just random errors derived from the judgment of the GRAs, which would be amended over time (Ederington, 1986). Alternately, split ratings are related to the GRAs' judgment on the banks' credit risk based on their rating methodology. Thus, rating disagreements can be the consequence of differences in the rating standards of the GRAs (see Cantor and Packer, 1997) or can also be related to some bank characteristics that may cause uncertainty about the banks' credit risk, leading to differences in the credit opinions of the GRAs (see Morgan, 2002; Iannotta, 2006). Considering both perspectives on the causes of split ratings, the first research question is: 'What are the drivers of GRAs' split bank ratings?' This Chapter uses as asset opacity proxies a selection of financial ratios (see section 5.4.2 for further information), following Morgan (2002) and Iannotta (2006).

Shen et al. (2012) show that GRAs assign lower bank ratings in emerging economies compared to the bank ratings in developed economies, even when financial ratios remain the same because GRAs are influenced by the country's information asymmetry (or opacity). Following this argument, financial ratios would have less influence on split bank ratings in emerging countries, as GRAs would assign a higher weight to the economic development and the degree of transparency of the institutions, which is generally low in those countries. This counterargument to the opacity hypothesis is also tested in the empirical analysis (see Section 5.4). Thus, *Hypothesis 1A* is:

Hypothesis IA $_{null}$.	Split bank ratings are explained by random rating errors.
Alternative hypothesis.	Information asymmetry (information opacity) strongly influences split bank ratings between GRAs in emerging economies.

The current Chapter is focused on the alternative hypothesis because the literature has already established that split bank ratings are not caused by random errors. Livingston et al. (2008) and Bowe and Larik (2014) show that rating disagreements often continue throughout the year, suggesting that the persistence of the rating disagreement is not caused by random errors of the rating process but differences of rating opinions between GRAs.

Morgan (2002) shows that Moody's consistently assigns lower ratings than S&P in corporate bonds with split ratings, labelling the behaviour the "lopsided effect". Livingston et al. (2007) test the lopsided effect using non-banking bond issues, dividing the sample between opaque and transparent issues and finds that Moody's consistently assigns lower ratings than S&P in the opaque sample. Similar evidence is found by Livingston et al. (2010) and Bowe and Larik (2014). This study examines if, when split ratings occur, one of the GRAs tend to assign consistently more conservative ratings than the other GRA because of bank opacity. *Hypothesis 1B* is as follows:

Hypothesis IB $_{null}$.	There is no evidence of lopsided ratings in any GRA when the banks have split ratings.
Alternative hypothesis.	Split bank ratings are characterized by being lopsided as a consequence of the issuer's opacity.

The second research question is: 'What is the effect of split bank ratings on the future bank rating migrations?'. According to Livingston et al. (2008) and Alsakka and ap Gwilym (2010c), since asset opacity is the main driver of split ratings, additional information on the issuer would decrease the uncertainty or information asymmetry, leading to future rating changes. They also find that the GRA that assigns the lower (higher) initial rating is more likely to upgrade (downgrade) the issuer in the next year. Thus, aspects such as reputation concerns or the competition between GRAs could also be plausible explanations of rating migrations, although they are not openly discussed in those investigations. Examining the GRAs' rating practices is beyond the scope of the thesis, but by considering each pair of GRAs and rating changes of each GRA after the occurrence of split ratings, this Chapter discusses the sensitivity of rating migrations to split ratings and also examines the direction of the rating migration. Furthermore, the larger the split ratings' differences (in notches), the stronger the impact on future rating changes, as the opacity would be higher. Thus, *Hypothesis II* is as follows:

Hypothesis II $_{null}$.	Split bank ratings do not influence the future bank rating migrations.
Alternative hypothesis.	Split bank ratings have a significant impact on future bank rating migrations.

5.4 Data

5.4.1 Rating data

The study employs quarterly long-term foreign-currency issuer credit ratings from October 2008 to December 2015, for banks domiciled in 11 emerging economies. The countries and the sample period are selected based on financial data availability in the Bankscope database, namely Argentina, Brazil, China, Colombia, Indonesia, Kazakhstan, Mexico, Nigeria, Russia, South Africa, and Thailand. The dataset is built upon the data collected for Chapter 4, from Interactive Data Credit Ratings in Emerging Markets (Henceforth, ID-CREM) and CapitalIQ. For the current Chapter, only banks with quarterly ratings assigned by at least two of the three GRAs (S&P, Moody's, and Fitch) are included in the sample. In comparison with Chapter 4, Chapter 5 is focused on examining split bank ratings using GRAs' GSR assigned to banks and does not investigate the split bank ratings using NSRs from GRAs or from NRAs. This is driven by the unavailability of historical data on NSR assignments by Fitch and by Moody's in the ID-CREM database (and the costs and difficulties of using any alternative data source). Since the focus of this Chapter is to examine the disagreements between GRAs in GSRs, NSRs assigned by NRAs are not relevant to answer the research questions.

Following the approach used by Alsakka and ap Gwilym (2010a), the credit rating scale of each GRA is transformed into an 18-point[100] numerical scale.[101] Quarterly rating disagreements correspond to the absolute value of the notch differences between each pair of GRAs. There are 234 banks with at least one rating from a GRA, and from those, 158 banks are rated by at least two GRAs.

[100] Following the approach used by Alsakka and ap Gwilym (2010a), the credit rating scale of each GRA is transformed into numerical scale. Since the current Chapter employs the GSR from S&P, Moody's and Fitch, and Fitch does not use modifiers "+" or "-" in the categories CCC (value of 2 in the numerical scale) or below, the ratings are transformed into an 18-point numerical scale instead of the 20-point numerical scale used in Chapter 4 where only S&P ratings are used.

[101] According to the numerical scale presented by Alsakka and ap Gwilym (2010a), the rating categories in default or with high probability of default are grouped in one numerical rating to simplify the different scales used by the CRAs at the lowest categories and because they occur rarely. According to Fitch's methodology, the modifiers "+" or "-" are not assigned for categories below "B". Hence, the ratings from Fitch and S&P differ from the numerical rating "2". Thus, the numerical rating "2" is assigned to the ratings "CCC" assigned by Fitch, while for S&P the same number corresponds to the ratings "CCC+/CCC/CCC-", and for Moody's corresponds to the ratings "Caa1/Caa2/Caa3". Moreover, the numerical rating "1" is assigned to the ratings "CC/D/RD/D" assigned by Fitch, while for S&P the same number corresponds to the ratings "CC/C/D", and "Ca/C" for Moody's.

Figure 5.1 illustrates the distribution of the quarterly numerical bank ratings assigned by each pair of GRAs during the sampled period. A high proportion of the assigned ratings (almost 50% of the observations) are between BBB- and BBB+ (9 to 11 on the numerical rating scale), while the ratings below B- (below "3") represent around 4% of the total observations. The lowest rating is "2" (CCC-/Caa2/CCC for S&P, Moody's and Fitch, respectively). The highest bank rating assigned by S&P is "13" or A, and the highest rating assigned by Moody's or by Fitch is "14" (A1/A+). The average bank rating assigned by each GRA is BB+/Ba1 ("8" on the numerical rating scale).

Table 5.1, Panel A, reports the quarterly rating data by each pair of GRA. The sample rated by S&P and Moody's comprises 1,898 observations for 92 banks from 9 countries.[102] The sample rated by S&P and Fitch includes 1,767 observations for 90 banks from 10 countries.[103] The sample rated by Moody's and Fitch covers 2,423 observations for 111 banks from 10 countries.[104] The proportion of rating disagreements for each pair of GRAs is: S&P and Moody's (74.7%), Moody's and Fitch (69.3%), and S&P and Fitch (54.4%).[105] Alsakka and ap Gwilym (2010c) document that S&P and Moody's disagree in 59.4% of the sovereign ratings assigned in emerging economies, S&P and Fitch in 34.6% and Moody's and Fitch in 57.6% of the cases, during the period January 2000 - January 2008. For European banks, Iannotta (2006) shows that S&P and Moody's disagree in 36.7% of the cases (between 1993 and 2003). Livingston and Zhou (2016) show that 47.4% of the sample of European corporates have split ratings between those two GRAs (during the period 2000 - 2014).

The high proportion of splits in this Chapter compared to the studies in developed countries could be partially explained by differences in the weighting of sovereign risk in GRAs' global bank methodology. Another explanation could be the low level of institutional transparency in emerging economies, which has shown a relevant impact on the risk-taking behaviour of banks in emerging countries (Chen et al., 2015).

Table 5.1, Panel A, also shows that S&P assigns inferior ratings versus Moody's and Fitch in almost 80% of the split ratings cases. Figure 5.2 indicates that S&P tends to assign ratings in a

[102] Argentinean banks are excluded since they are not rated by both S&P and Moody's, Nigerian banks are removed from the sample rated by S&P and Moody's as they have only one observation during the period of analysis.
[103] Argentinean banks are excluded since not rated by both S&P and Fitch.
[104] Nigerian banks are removed from the sample rated by Moody's and Fitch as they have only one observation during the period of analysis.
[105] As the sampled banks can have multiple ratings, it is possible that the same bank has split ratings from different pairs of GRAs.

more conservative manner in investment grade categories (from “9” or BBB-/Baa3). For bank rated jointly by Moody’s and Fitch, Moody’s tends to assign lower ratings in speculative grades, while Fitch tends to assign lower ratings in the upper categories (above “10” or BBB). The conservativeness of S&P in bank ratings from emerging economies is also reported for European banks (except for Germany) by Iannotta (2006), while Morgan (2002) and Livingston et al. (2010) show evidence of Moody’s conservativeness in bank and corporate ratings in the US, respectively. In sum, the univariate analysis supports the lopsided hypothesis proposed by Morgan (2002), with S&P tending to assign lower ratings among the three GRAs when split ratings occur. The lopsided evidence is discussed further in the multivariate analysis (see Sections 5.5.2 and 5.6.2).

Additionally, Table 5.1, Panel A, presents the type of rating disagreements for each GRA in the sampled banks. Split ratings of one-notch are the most common case. Split ratings of three or more notches are scarce. Although not reported in the table, there are only two cases of split ratings where the first GRA assigns a rating four-or more notches lower than the second GRA. Firstly, the Development Bank of Kazakhstan, with a rating of BBB- from S&P and A2 from Moody’s (four-notch difference) in the last quarter of 2008. However, Moody’s downgraded the bank during the next two quarters (to Baa1 in the first quarter of 2009, and to Baa2 in the second quarter of 2009). Secondly, the Public Joint-Stock Company Rosbank, domiciled in Russia, had a BB+ rating from S&P and A- from Fitch (4-notch difference) during the last quarter of 2008. However, Fitch downgraded the bank to BBB+ in the second quarter of 2009. These two cases are an example of the follower’s behaviour of Moody’s and Fitch relative to S&P, further analysed in the multivariate analysis of the Chapter. The sample has also one case of a bank with split ratings of 5-notches. The ATF Bank in Kazakhstan had a rating of B1 by Moody’s while it was rated BBB by Fitch (5-notches lower) during the third quarter of 2012. The rating difference persisted until the second quarter of 2013, when Fitch downgraded it to BBB-. On the third quarter of 2013, Moody’s downgraded ATF Bank to Caa1, and Fitch followed downgrading the bank to B-. In the latter case, Moody’s showed a conservative behaviour relative to Fitch in speculative ratings.

Table 5.2 presents the number of quarterly observations with split bank ratings for each pair of GRAs, reported by country during the period of analysis. Brazil, Russia, Mexico, and Kazakhstan have the highest number of split bank rating observations in all pairs of GRAs. Split bank rating observations between S&P and Moody’s for Brazil are 23.6%, while for S&P and Fitch the highest number of split ratings observations are observed in Mexico (17.4%).

Russia has the highest number of split ratings by Moody's and Fitch (30.8%). Differences in the GRAs' opinions of the sovereign risk, in the macroeconomic and political situation of each country of the sample and in the quality of information available in each country, are the potential factors that could explain the high proportion of rating disagreements in those four countries. To control for the heterogeneity in the countries of the sample and the sovereign risk, the empirical models include a set of controls that are described in Section 5.4.4.

To analyse the impact of split bank ratings on bank rating migrations, a rating change is defined as a rating upgrade or a downgrade at the notch level by any of the GRAs, in any quarter of the sampled period. Table 5.3 reports quarterly rating changes by each GRA for each pair of GRAs. Overall, the number of downgrades is considerably greater than the number of upgrades for each pair of GRAs during the period of analysis. Two-notches rating changes, which are not common, occur much more frequently for Moody's relative to the other two GRAs. Nevertheless, the percentage of rating changes compared to the total number of observations is low (less than 9%), which indicates stability in ratings and confirms that GRAs have a "through-the-cycle methodology" (Altman and Rijken, 2004).

Figure 5.3 illustrates the distribution of rating changes of S&P, Moody's and Fitch. Downgrades are predominant between 2009 and the first quarter of 2010, possibly reflecting the worsening of the banks' financial situation caused by the financial crisis. After April 2010 and until the first quarter of 2013, rating upgrades are more common, possibly related to the sovereign upgrades of Brazil, China, Indonesia and Kazakhstan. The particular spike in the positive rating changes during the first quarter of 2012 reflects the bank rating methodology revision by S&P, which lead to upgrades in several banks from Russia (S&P, 2011c), and from China and Brazil (S&P, 2011d). The gradual increase in the number of downgrades since 2013 is likely related to the relaxation of the bond-buying program and tightening of the monetary policy of the U.S. Federal Reserve (taper tantrum) during 2013, which increases the volatility of capital flows to emerging economies (UNCTAD, 2017),

5.4.2 Financial variables

In the literature of split ratings, there are different approaches to measure asset opacity. For instance, Livingston et al. (2007) construct an asset opacity index (OI), using the average weight of: firm size, market to book ratio and intangible assets (financial ratios), the standard deviation of analysts' earnings forecasts, the number of stock analysts, the bid-ask spread as a percentage of the stock price issued by the firm (called adverse selection), and the bond maturity. A similar approach is used by Livingston and Zhou (2016), although the study only uses four variables as proxies of asset opacity, to avoid noise in their estimations: firm size, the standard deviation of analyst forecasts, analyst forecast errors, and stock return volatility. Other studies use financial and accounting variables as proxies of opacity (e.g. Morgan, 2002; Iannotta, 2006; Livingston et al., 2007, 2010; Hyytinen and Pajarinen, 2008; Livingston and Zhou, 2010, 2016; Bowe and Larik, 2014; Ismail et al., 2015; Jiang and Packer, 2019).

For many emerging countries, the analysts' earnings forecasts and data on the number of stock analysts are not available. Therefore, the current Chapter examines information opacity using a set of financial ratios, which are selected based on the available literature on split ratings, literature on the determinants of bank ratings (Gropp and Heider, 2010; Bellotti et al., 2011; Bissoondoyal-Bheenick and Treepongkaruna, 2011; Caporale, 2012; Shen et al., 2012; Hau et al., 2013), and the published bank rating methodologies of the GRAs. The financial ratios selected as a proxy for information opacity are: bank size, capital, profitability, and liquidity.[106] The quarterly financial information is available from Bankscope (see further details in Table 5.5). Because current values of the financial variables could reflect additional information that was unknown when the rating was assigned (Salvador et al., 2014), the financial variables are lagged four quarters (t-4), following prior literature (Iannotta, 2006; Livingston et al., 2018; Jiang and Packer, 2019). The description of the variables is as follows.

Size corresponds to the natural log of total assets, and it is a variable commonly used in bank's rating literature (e.g. Jiménez et al., 2010; Haselmann and Wachtel, 2011; Bae et al., 2013; Hau et al., 2013). The variable total assets is measured in thousands of USD and has been converted using the exchange rate prevailing at the date of each report (closing date of the statement).[107] Larger banks commonly disclose more information as they have lower information costs than smaller banks, and their size prevents them to have a competitive disadvantage when releasing information (Di Pietra et al., 2014). Weiß et al. (2014) find that bank size is not significant in explaining the systematic risk after the subprime crisis, as larger banks are subject to more stringent supervision after the crisis. Since stronger regulation implies less uncertainty for

[106] The number of banks in emerging economies listed in stock exchanges is reduced and the analysts forecast data available in Datastream covers only 2017. Hence, is not possible to use the proxies of opacity proposed by Livingston and Zhou (2016).
[107] According to Bankscope, the exchange rates are sourced from the International Monetary Fund (IMF) website. They refer to the closing date of the statement. The exchange rates are from the IMF and are updated monthly. They correspond to the rate valid at the closing date of the month.

GRAs, an increase in the bank size decreases the probability of split ratings. Considering both arguments, it is expected that larger banks have less split bank ratings. Hence, a negative sign for the *Size* coefficient is expected. Nevertheless, the literature also argues that larger size banks tend to be more complex, therefore GRAs' uncertainty about their creditworthiness is greater and the likelihood of split ratings is higher (Morgan, 2002; Iannotta, 2006). Moreover, Hau et al. (2013) show that GRAs' ratings have a positive rating bias when rating large banks, arguing that the distortions could be related to their systemic importance ("too big to fail") or because large banks are often part of a financial group, which represents additional rating business for the GRAs. They show that large banks are often rated by more than one GRA when the rating assign by one GRA is not favourable. Thus, larger banks with multiple ratings would have a higher probability of split ratings. Following these arguments, *Size* coefficient is expected to have a positive sign.

Capital is the ratio of equity to total assets. It measures the percentage of the company's assets owned by the shareholders (equity capital). Banks use the capital as a buffer against default (Shen et al., 2012) and it is a proxy of the potential growth of a firm (Han et al., 2012). Morgan (2002) finds that the ratio of capital to total assets of US banks decreases the probability of split bond ratings between S&P and Moody's, arguing that banks with high capital ratio tend to be conservative in their business strategy and to have better asset quality than banks with high leverage. Following Morgan (2002), a higher capital ratio would decrease the probability of split ratings, thereby the sign of *Capital* coefficient is expected to be negative. Nevertheless, Bowe and Larik (2014) show that higher leverage (ratio of debt to total assets) decreases split corporate ratings between S&P and Moody's, arguing that these GRAs possibly have a similar perception on the worsening of the credit quality conditions of the corporates, reducing the rating disagreements between GRAs. However, they also argue that split ratings can be observed if the leverage ratio improves. Following Bowe and Larik (2014), if GRAs have a different perception of the improvements in the credit quality when the bank capital increase (or the bank is less leveraged), the probability of rating disagreements would increase and the *Capital* coefficient is expected to have a positive sign.

Profitability corresponds to the return on average assets (ROAA) and is an indicator of the bank's ability to manage its assets and make profits. The literature shows that the return on assets (ROA) is a good proxy of bank risk-taking behaviour, which in turn has a positive relation with bank opacity (see Fosu et al., 2017). Since the objective in Chapter 5 is to study the effect of opacity in bank rating disagreements, instead of the ratio of net interest income to average earning assets (Netinterest) used in Chapter 4, the current Chapter incorporates the ROAA as the proxy of profitability. In split rating literature, profitability is a significant driver of corporate split ratings. Bowe and Larik (2014) find that larger firms with high profitability have a lower likelihood of a split ratings, and Jiang and Packer (2017) find that profitability has a high positive impact on the ratings assigned by NRAs that have partnerships with GRAs, while the weight of this variable is not significant for local NRAs. Following these arguments, a negative sign is expected as higher profitability would reduce GRAs' uncertainty and thus, reduce the probability of split ratings.

Liquidity corresponds to liquid assets to deposits and short-term funding ratio and is a proxy of the bank's obligations that would be met if unexpected withdrawals happened. Iannotta (2006) finds that liquid assets are negatively related to split ratings, as these assets are perceived as more transparent and measurable assets, thus, higher liquidity generates less uncertainty when rating a bank. Also, Bissoondoyal-Bheenick and Treepongkaruna (2011) find that greater liquidity is associated with higher ratings, as it mirrors the banks' flexibility. If liquid assets hedge part of the risk exposure in case of unexpected financial stress, GRAs should see higher liquidity as less uncertainly, hence the coefficient of *Liquidity* is expected to have a negative sign.

5.4.3 Matching process between bank credit ratings and financial information

To test *Hypothesis IA* and *IB*, the bank rated sample (158 banks), which is obtained from ID-CREM and CapitalIQ is matched with the data of the selected financial ratios, which is collected from Bankscope. Then, the financial variables are trimmed to identify and remove extreme values. Observations with either *Size*, *Capital* or *Profitability* below 0.5 and above 99.5 percentile are removed, while for liquidity, observations below 0.5 and above 98.5 percentile are removed. Moreover, banks with only one observation during the period are removed from the sample. Table 5.1, Panel B, presents the final matched sample after the trimming process. There are 78 banks with quarterly financial information rated by S&P and Moody's (862 observations), from 9 countries (71 of those banks have split ratings at least in one quarter). From the sample rated by S&P and Fitch, 76 banks with quarterly financial information matched with the ratings (798 observations), from 10 countries (66 of those banks have split ratings at least in one period). Finally, for the sample rated by Moody's and Fitch, there are 64 banks with matched rating information with quarterly financial information (813 observations) from 9 countries (of which 62 banks have split ratings at least in one period).[108] The highest number of rating divergences (76.1%) occur between S&P and Moody's, S&P and Fitch disagree in 56.5% of the total number of observations, while Moody's and Fitch have different risk assessments in 66.4% of the observations.

Table 5.4 presents the mean differences between the non-split and split-rated samples during the period of analysis for each pair of GRAs. The results show that bank observations with split ratings between each pair of GRAs have a larger *Size* and lower *Liquidity* compared to the non-split sample. The bank observations with split ratings by S&P and Moody's, and by Fitch and Moody's have higher *Capital*, while non-split bank observations have higher *Capital* in the sample rated by S&P and Fitch. The bank observations with split ratings by S&P and Moody's and S&P and Fitch have higher *Profitability*, while for Moody's and Fitch the higher *Profitability* occurs in the non-split sample. The average numerical rating for split-rated observations is between 9 and 10 for the three pairs of GRAs (9 corresponds to the lowest investment grade: BBB-/Baa3). The observations with split ratings between S&P and Moody's and between S&P and Fitch have higher ratings than non-split observations, while the difference in the average rating between the non-split and split bank rating observations by Moody's and Fitch is marginal. Because the variables are not normally distributed, the Wilcoxon rank-sum test (also called Mann-Whitney U test) is applied. Except for the *Liquidity* in the sample rated by S&P and Moody's and the *Profitability* in the sample rated by Moody's and Fitch, the mean differences between the split and non-split sample are not statistically significant as expected, which means that there are no substantial differences in the financial profiles of the bank observations with split ratings and without split ratings. Nevertheless, the particular characteristics of the split and non-split samples are preliminary evidence of the effect of asset opacity on the GRAs' rating changes.

5.4.4 Other explanatory variables

To control for possible differences in the economic, financial and political environment of the countries of the sample, the following variables are included in the models (see further details in Table 5.5).

[108] For S&P and Moody's and Moody's and Fitch, Argentinean banks are excluded because they do not have financial information reported in Bankscope during the period of analysis. Nigerian banks are excluded because there is only one observation during the period of analysis.

Domestcredit corresponds to the ratio of Bank domestic credit/GDP and is included to control for the country's banking sector depth and development (Williams et al., 2015). It is expected that for the banking sector with more depth and development, GRAs are less likely to differ in their assigned bank ratings, as the country will show more transparency and less volatility (Rose and Spiegel, 2009).

To account for the macroeconomic and financial environment of each country, the empirical model~~s~~ incorporate the variable *Sovereign*, which corresponds to the average sovereign rating assigned to each country where the bank is domiciled by the three GRAs, based on the 18-point numerical rating scale (following Alsakka and ap Gwilym, 2010a). Williams et al. (2013) show that sovereign ratings represent an upper boundary for bank ratings in emerging economies (the sovereign ceiling effect). Moreover, they find that the probability of bank rating downgrades is higher in countries with low sovereign ratings than in countries with better sovereign ratings. Since GRAs reflect their perception of low sovereign credit quality and weak economic management in lower sovereign ratings (see S&P Global Ratings, 2016), it is expected that weaker sovereign ratings would signal a more unstable macroeconomic environment, which increases the uncertainty of the banking sector's financial performance. Thus, higher sovereign ambiguity (lower sovereign ratings) would increase the likelihood of bank rating disagreements. Thus, a negative sign is expected for the coefficient of *Sovereign*.

Ownership is defined as equal to one if the bank is privately-owned or zero if the bank is state-owned. The inclusion of the variable follows prior credit ratings literature, which shows that the firms' type of ownership influences their ratings (e.g. Williams et al., 2013; Correa et al., 2014). Correa et al. (2014) show that state-owned banks have a higher probability of receiving government support compared to private banks, as a bank only receives this support if it is systemically important. Public ownership possibly reduces the uncertainty that GRAs are facing when evaluating government support, leading to less rating disagreements, hence a positive sign is expected. However, Jiang and Packer (2017) point out that the literature has ambiguous views regarding GRAs' perceptions on ownership: state-owned firms might show stronger creditworthiness due to the possibility of receiving state support, however, they may also have greater credit risk when the economy is facing a period of financial distress. They find that state-ownership is perceived more positively by GRAs (S&P and Moody's) than by local Chinese CRAs. Following Jiang and Packer (2017), greater sovereign risk could be a sign of higher uncertainty, leading to more (less) frequent split ratings in state-owned (private-owned) banks. However, with better government perception, private ownership would lead to more frequent split ratings than state ownership. Because the current study has sampled countries with different levels of economic development and sovereign risk, the expected sign of private ownership could be positive or negative.

Because the countries in the study sample can have differences in institutional transparency (or government corruption), a measure of corruption is included as a control variable. Chen et al. (2015) finds that government corruption is a critical variable when studying bank risk-taking behaviour, including in their study two different measures of governmental transparency: The Control of corruption Index (*CCI*), which is a sub-index of the Worldwide Governance Indicators (WGI) prepared by the World Bank, and the Corruption index (CI) estimated by Transparency International, which is an average of different surveys (Transparency International, 2016). *CCI* has a range between -2.5 to +2.5 from the most corrupt to the less corrupt and *CI* has a scale from 0 to 10, from the most corrupt to the less corrupt. Chen et al. (2015) rescale *CCI* by subtracting the index from zero, to show that higher values indicate more corruption, and also rescale *CI*.[109] Following Chen et al. (2015), this Chapter includes both *CCI* and *CI* rescaling the variables also, to show that higher values correspond to less transparency and higher corruption in the countries where the banks are located. An increase in *CCI* or *CI* would increase bank risk exposure. Hence, the coefficient of *CCI* or *CI* is expected to have a positive coefficient.

Finally, to capture the impact of the previous rating status (speculative versus investment grade), on the current rating disagreement between GRAs, the estimation includes the variable *Invrating*. Alsakka and ap Gwilym (2010a) find that the threshold between speculative and investment grade has a significant impact on future rating changes. In the current Chapter, to evaluate the effect of the prior rating level on the rating disagreements between GRAs, there are two possible definitions of the variable: i) The average numerical rating (based on the 18-point numerical scale) assigned to bank *i* by two particular GRAs, and ii) A dummy variable named *Invrating*, that takes the value of 1 if the bank is rated at investment-grade (above 9 or BBB- for S&P and Fitch or Baa3 for Moody's) at time t-4, based on the average numerical rating of each pair of GRA, and 0 if the bank is rated at speculative-grade. Panels A, B, and C of Figure 5.2 show that the majority of the split ratings for the sampled banks occur at the threshold between speculative and investment grade categories. Therefore, this Chapter uses

[109] Chen et al. (2015) rescale the Corruption index (CI) by deducting 10 from the score and then dividing it by the mean of the corruption annual index for all countries, to consider changes in the methodology or surveys that affect the score.

the second definition, i.e. a dummy variable, because it captures the effect of the investment-speculative rating threshold. It is expected that banks that are rated at the investment-grade level are less likely to have split ratings (negative sign).

Although these control variables are selected based on the data availability and following previous literature examining emerging economies, there might be alternatives to the selected control variables that can be used to measure the country level opacity in future studies. For instance, the economic freedom index from the Heritage Foundation is an index that measures the quality of economic freedom per country. The economic freedom index evaluates the legal environment, government transparency, financial freedom, and regulatory framework, and has previously been used by Williams et al. (2015), to analyse the effect of the sovereign ceiling on bank ratings from emerging economies. In the current Chapter, this index is not used because Chen et al. (2015) show that corruption is detrimental for financial stability regardless of the low or high economic freedom. Thus, the corruption index is more suitable in comparison to the economic freedom index as a measure of opacity at the country level for use in this thesis. Other examples of alternative variables that could be used as measures of opacity are the law and order tradition and the level of bureaucracy, which are proxies of the institutional environment presented by Shen et al. (2012). They are not included in the current study because they are collected from a subscription-based database named International Country Risk Guide.

5.4.5 Summary statistics

Table 5.6 reports the summary statistics on the variables used in the multivariate analysis for each pair of GRAs (Panel A: S&P and Moody’s, Panel B: S&P and Fitch, Panel C: Moody’s and Fitch). Panels A, B and C show that the average *Size* of the banks is similar between each pair of GRAs. The mean of *Capital* is lower for banks rated by Moody’s and Fitch, suggesting that banks rated by those GRAs have higher leverage than banks rated by the other two pairs of GRAs. *Profitability* measured by ROAA is between 1.2% and 1.4%, which indicates a high level of profitability in emerging economies compared with the ROAA of 0.5% reported in high income countries (Dietrich and Wanzenried, 2014). The average of *Liquidity* is between 30% and 31% for all three samples, which is low compared to the 10-year (2001-2011) average liquidity of 47.8% reported for European banks (Beccalli et al., 2015).

Panels A, B, and C of Table 5.6 show that the standard deviation of the financial variables is similar for the three pairs of GRAs. *Domestcredit* is the variable with the highest volatility, showing the heterogeneity of the countries in the sample. The average numerical bank rating of the sample corresponds to BBB-, which is the lowest investment grade category: 9.2 for S&P and Moody's and for S&P and Fitch, and 9.6 for Moody's and Fitch.[110]

The variable *Sovereign* has a low standard deviation and has an average numeric rating of 10.7 for S&P and Moody's and for Moody's and Fitch, and 10.6 for S&P and Fitch, equivalent to a sovereign rating of BBB. The lowest sovereign rating corresponds to Nigeria (5.5 or BB-/Ba3), reported from the first quarter of 2009 to the fourth quarter of 2012, while China has the highest rating (14.6 or AA-/Aa3), which has not changed since the first quarter of 2011. According to Kaufmann et al. (2010), the corruption index calculated by the World Bank shows the perceptions of the extent to which public power is exercised for private gain. For the countries of the sample, the average corruption index (CCI) is 0.4 for S&P and Moody's and 0.5 for S&P and Fitch and Moody's and Fitch, which is a medium level according to the range presented by the World Bank, and the country with the highest corruption index is Russia.

Panels A, B and C of Table 5.7 report the pairwise correlation matrix for the lagged explanatory variables (t – 4) for each pair of GRAs. As expected, the highest correlation occurs between *CCI* and *CI* because the variables are alternative measures for the level of corruption in each sampled country. Thus, Equations 5.1 to 5.3 (see Section 5.5.1) are estimated using two models: Model I includes *CCI*, and Model II includes *CI*. Otherwise, there is no evidence of multicollinearity.

[110] According to the information collected from ID-CREM database, the lowest rating (2 or CCC-/Caa2) assigned by S&P and Moody's corresponds to the Russian Standard Bank JSC during the last quarter of 2015. TsesnaBank JSC from the Republic of Kazakhstan received a 3 (B-) from S&P and 2 (CCC) from Fitch during the second quarter 2009. Banco Macro SA from Argentina has the lowest rating assigned by Moody's and Fitch (2 or Caa2/CCC), assigned in the last quarter of 2014.

5.5 Methodology

To answer the research questions presented in Section 5.3, the study employs a binary probit approach, using different subsamples. Hypothesis 1A and Hypothesis 1B, require using the available quarterly financial and rating data. As a result, both Hypotheses use the matched bank sample described in Section 5.4.3. Hypothesis II is focused on the effect of split ratings on the future rating changes of GRAs, employing the total rating dataset before matching it with financial information (see Table 5.3 for the details of the rating changes).

5.5.1 Hypothesis IA: causes of split bank ratings

To address whether information asymmetries and economic instability are factors that cause split ratings between each pair of GRAs, the study employs a binary probit model, which has been used previously to analyse split ratings (Morgan, 2002; Bowe and Larik, 2014). In the binary probit model, the latent variable Split* can be interpreted as the propensity to have split ratings rather than assigning the same rating when the bank is rated by two GRAs.[111] Following Greene (2012), the propensity to be assigned split ratings is given by the following specification:

$$Split^{*}_{i,j,t} = \alpha X_{i,j,t-4} + \beta_k Controls_{j,t-4} + \delta YD + \theta CD + \varepsilon_{ijt} \qquad (5.1)$$

*Split** is an unobserved latent variable that is linked to the observed response variable *Split* by the measurement model:

$$Split_{i,j,t} = 1 \; if \; Split^{*}_{i,j,t} > 0$$

$$Split_{i,j,t} = 0 \; if \; Split^{*}_{i,j,t} \leq 0$$

The subscripts i, j, t denote bank, country and time (quarters), respectively. The binary variable $Split_{i,j,t}$ takes the value of one when the difference between the quarterly bank ratings assigned by two GRAs is non-zero, and zero when the ratings assigned by both GRAs are equal.

$X_{i,j,t-4}$ corresponds to the financial ratios selected as opacity proxies: *Size*, *Capital*, *Liquidity*, and *Profitability*, lagged four quarters to reduce endogeneity and reverse causality issues (See Section 5.4.2 for the definition, rationale and expected sign of each financial variables). $Controls_{i,k,t}$ is a set of variables that control country-specific characteristics (See Section 5.4.4

[111] Eqs. (5.1) to (5.6) are estimated for each pair of GRAs: S&P and Moody's, S&P and Fitch and Moody's and Fitch.

for the rationale and expected sign of the variables). To consider both proxies of the corruption index, Eq. (5.1) is estimated using two different models: Model (I) includes the index *CCI*, while Model (II) includes the index *CI*.

To partial out country-specific time invariant unobserved effects and control for time shocks that might affect the banks in the sample, the estimations of Eq. (5.1) incorporate a set of year and country dummies (*YD* and *CD*). Moreover, concerns on heteroscedasticity and serial correlation in the error terms are addressed by Huber-White robust standard errors (see Section 4.5.1). While not reported in the Chapter, Eqs. (5.1) and (5.2) are also estimated using clustered standard errors at the bank level, and similar results are obtained. In addition, marginal effects (MEs) are calculated on statistically significant variables (at 5% level or better) for Eqs. (5.1) to (5.5), using the STATA command "Margins" following Williams (2012). For statistically significant binary regressors, the MEM for categorical variables show how P(Y=1) changes as the categorical variable changes from 0 to 1, holding all other variables constant at their sample means. For continuous regressors, the economic significance of the variables is evaluated by calculating their elasticities (a 1% change), evaluated at the sample mean of the regressors. For further details on MEs and the rationale for estimating MEs see Section 4.5.1.

5.5.2 Hypothesis IB: conservativeness hypothesis

The univariate analysis discussed in Section 5.4.1 suggests that S&P tend to be the most conservative GRA. In order to test if the opacity proxies can explain the tendency of bank ratings to be lopsided, a binary probit model with fixed-effects is estimated following Livingston et al. (2010), and Bowe and Larik (2014). Furthermore, consistent with those studies and the approach in Vu et al. (2015), cases where GRA1 assign a "superior rating" are considered separately from cases where GRA1 assign an "inferior rating", for each pair of GRAs. Thus, the latent variable $GRA1Sup^{*}$ can be interpreted as the propensity for GRA1 to assign a higher rating to a bank *i* for banks that have split ratings,[112] and is specified as follows:

$$GRA1Sup^{*}_{i,j,t} = \alpha X_{i,j,t-4} + \beta_k Controls_{j,t-4} + \delta YD + \theta CD + \varepsilon_{ijt} \quad (5.2)$$

*GRA1Sup** is an unobserved latent variable that is linked to the observed response variable *GRA1Sup* by the measurement model:

[112] In Equations (5.2) and (5.3), for the first two pairs of GRAs, namely, S&P and Moody's and S&P and Fitch, *GRA1* corresponds to S&P, while for Moody's and Fitch, *GRA1* corresponds to Moody's.

$GRA1Sup_{i,j,t} = 1\ if\ GRA1Sup^*_{i,j,t} > 0$

$GRA1Sup_{i,j,t} = 0\ if\ GRA1Sup^*_{i,j,t} \leq 0$

The subscripts i, j, t denote bank, country and time (quarters), respectively. The binary variable $GRA1Sup_{i,j,t}$ takes the value of one when a bank is split rated and GRA1 assigns a superior rating compared to the rating assigned by GRA2, and zero when both GRAs assigned equal ratings or GRA1 assigns an inferior rating.

Equation (5.3) presents the specification for inferior ratings from GRA1. Namely, the latent variable $GRA1Inf^*$ can be interpreted as the propensity for GRA1 to assign a lower rating to a bank *i* for banks that have split ratings. The propensity to be assigned split ratings is given by the following specification:

$$GRA1Inf^*_{i,j,t} = \alpha X_{i,j,t-4} + \beta_k Controls_{j,t-4} + \delta YD + \theta CD + \varepsilon_{ijt} \quad (5.3)$$

*GRA1Inf** is an unobserved latent variable that is linked to the observed response variable *GRA1Inf* by the measurement model:

$GRA1Inf_{i,j,t} = 1\ if\ GRA1Inf^*_{i,j,t} > 0$

$GRA1Inf_{i,j,t} = 0\ if\ GRA1Inf^*_{i,j,t} \leq 0$

Where the subscripts i, j, t denote bank, country and time (quarters), respectively. The binary variable $GRA1SInf_{i,j,t}$ takes the value of one when a bank is split rated and GRA1 assigns an inferior rating compared to the rating assigned by GRA2, and zero when both GRAs assigned equal ratings or GRA1 assigns a superior rating.

Consistent with Bowe and Larik (2014), to evaluate if the banks' opacity is a driver of the conservative rating behaviour, the model incorporates the same explanatory and control variables included in Eq. (5.1). Eq. (5.2) and (5.3), and also include a set of year and country dummies (YD and CD) and are estimated using CCI (*Model I*), and CI (*Model II*).

5.5.3 Hypothesis II: Split bank ratings and future bank rating migrations

This Section evaluates if banks with split ratings are more susceptible to show future rating changes than non-split banks, which are considered more transparent. Additionally, it also examines if the magnitude of the split ratings in notches has a different effect on the rating migrations, as higher notches-differentials would signal higher opacity. The rationale for

Hypothesis II follows Livingston et al. (2008), and extends the methodology for studying split sovereign and rating migrations by Alsakka and ap Gwilym (2009, 2010c).

To test *Hypothesis II*, the study employs a binary probit model approach because of the few observations in the sample with more than one notches upgrades and downgrades (see Table 5.3).[113] Rating upgrades are separated from downgrades, as the literature has shown that key differences exist between them (Gande and Parsley, 2005; Ferreira and Gama, 2007; Williams et al., 2015; Alsakka et al., 2017). Let *UpgGRA** represent the propensity of bank *i* to be upgraded by a GRA rather than maintaining the same rating. This propensity to be upgraded is specified as follows:

$$UpgGRA^{*X}_{i,j,t} = \beta_1 1NSupGRA1_{i,j,t-1} + \beta_2 2NSupGRA1_{i,j,t-1} + \beta_3 1NInfGRA1_{i,j,t-1} + \beta_4 2NInfGRA1_{i,j,t-1} + \gamma_h \sum_{h=1}^{18} Rating_{i,h,t} + \delta YD + \theta CD + \varepsilon_{ijt} \quad (5.4)$$

*UpgGRA** is an unobserved latent variable that is linked to the observed response variable *UpgGRA* by the measurement model:

$$UpgGRA_{i,j,t} = 1 \; if \; UpgGRA^{*}_{i,j,t} > 0$$

$$UpgGRA_{i,j,t} = 0 \; if \; UpgGRA^{*}_{i,j,t} \leq 0$$

The subscripts i, j, t denote bank, country and time (quarters), respectively. The binary variable $UpgGRA_{i,j,t}$ takes the value of one if GRA X (GRA1 or GRA2) upgrades the bank by one or more notches, zero if the rating assigned by GRA X (GRA1 or GRA2) has not changed since the previous quarter.

The effects of the split bank ratings on future downgrades are estimated using a separate model. Thus, the second model incorporates *DownGRA** which represents the propensity of bank *i* to be downgraded by a GRA rather than maintaining the same rating. This propensity to be downgraded is specified as follows:

$$DownGRA^{*X}_{i,j,t} = \beta_1 1NSupGRA1_{i,j,t-1} + \beta_2 2NSupGRA1_{i,j,t-1} + \beta_3 1NInfGRA1_{i,j,t-1} + \beta_4 2NInfGRA1_{i,j,t-1} + \gamma_h \sum_{h=1}^{18} Rating_{i,h,t} + \delta YD + \theta CD + \varepsilon_{ijt} \quad (5.5)$$

*DownGRA** is an unobserved latent variable that is linked to the observed response variable *DownGRA* by the measurement model:

$$DownGRA_{i,j,t} = 1 \; if \; DownGRA^{*}_{i,j,t} > 0$$

[113] An ordered probit model is included in Section 5.6.4 as robustness test.

$DownGRA_{i,j,t} = 0 \ if \ DownGRA^{*}_{i,j,t} \leq 0$

The subscripts i, j, t denote bank, country and time (quarters), respectively. The binary variable $DownGRA_{i,j,t}$ takes the value of one if the GRA X (GRA1 or GRA2) downgrades the bank by one or more notches, and zero if the rating assigned by GRA X (GRA1 or GRA2) has not changed since the previous quarter.

Table 5.1, Panel A, confirms that the magnitude of split ratings between each pair of CRAs is usually of one notch, and the cases of three or more notches are rare. Hence, superior split ratings of more than one notch are grouped in $2NSupGRA1$ and inferior split ratings of more than one notch are grouped in $2NInfGRA1$. Thus, the definition of the covariates in Eqs. (5.4) and (5.5) is as follows:

$1NSupGRA1_{i,j,t-1}$ is a dummy variable that takes the value of one if the bank has one-notch higher rating by GRA1 than GRA2 in the last quarter (t-1).

$2NSupGRA1_{i,j,t-1}$ is a dummy variable that takes the value of one if the bank has a more-than-one-notch higher rating by GRA1 than GRA2 in the last quarter (t-1).

$1NInfGRA1_{i,j,t-1}$ is a dummy variable that takes the value of one if the bank has one-notch lower rating by GRA1 than GRA2 in the last quarter (t-1).

$2NInfGRA1_{i,j,t-1}$ is a dummy variable that takes the value of one if the bank has a more-than-one-notch lower rating by GRA1 than GRA2 in the last quarter (t-1).

$Rating_{i,h,t-1}$ is the rating level assigned to the bank *i* by the GRA1 at time *t-1* (last quarter) based on the 18-point numerical scale.

The estimation incorporates year and country dummy variables (*YD* and *CD*). Concerns on heteroscedasticity and serial correlation in the error terms are addressed by Huber-White robust standard errors (see Section 4.5.1). MEs are calculated for the economic significance of the explanatory variables. Moreover, Eq. (5.4) and Eq. (5.5) are estimated using Huber-White robust standard errors (Model I) and using clustered standard error at the bank level, to account for any within-bank correlation that has not been captured by the fixed effects (Model II).

5.6 Empirical results

5.6.1 The drivers of split bank ratings

Tables 5.8 to 5.10 present the results of the estimations of Eq. (5.1), for each pair of GRAs. To assess the economic significance of the variables, the marginal effects at the mean (MEM) are estimated for those variables which demonstrate statistical significance. Model (I) includes the index *CCI*, while Model (II) includes the index *CI*. In general, adding a different proxy of corruption has no material impact on the estimations, except for split ratings between S&P and Moody's, an aspect that is discussed in the results reported in Table 5.8.

Table 5.8 reports the results for the sample rated by S&P and Moody's. Both Models I and II show that the *Size* coefficient is positive as expected and highly significant. Banks with larger *Size* are more likely to have split ratings between S&P and Moody's. The significance of *Size* is aligned with the results by Morgan (2002) and Iannotta (2006), thus contributing to the debate in the literature by showing that in emerging economies, GRAs consider the complexity of the bank business to be a relevant risk factor. The *Capital* coefficient is positive and significant at the 10% level in Model I and at the 5% level in Model II. The positive sign of the *Capital* coefficient is aligned with the findings of Bowe and Larik (2014), suggesting that GRAs have different perceptions about the bank's capacity to absorb losses, which is reflected in rating disagreements. Additionally, *Profitability* is only significant in Model II and with a negative sign, showing that an increase in profitability decreases the likelihood of rating divergences between the two GRAs, which is aligned with the findings in prior literature. According to the marginal effects, a 1% change in the natural log of *Size* at its mean, which is an increase from US$38,796 million to US$ 46,205 million, would increase the likelihood of split ratings by 1.2% in Model I (1.32% in Model II). Moreover, a 1% change in *Capital* increases the probability of split ratings by 0.12% in Model I (0.16% in Model II), while the same change in *Profitability* decreases the likelihood of split ratings by 0.49% in Model II.

Table 5.8 also presents significant differences in the statistical significance of the corruption proxy between Model I and Model II. Although both proxies have the expected positive sign, *CCI* is not statistically significant in Model I, while *CI* is highly significant in Model II. Specifically, in Model II a 1% change in the corruption index is perceived negatively by GRAs, as expected, and increasing the probability of observing rating disagreements by 3.26%. The different approaches taken by S&P and Moody's when incorporating the effects of corruption within their rating methodologies could explain the difference in the statistical significance of

CCI and CI. While Moody's incorporates explicitly only the index CCI in the evaluation of institutional strength within its bank rating methodology (Moody's, 2018a), S&P considers the economic risk evaluation, the World Bank Governance indicators for Control of Corruption and Transparency International's 'Corruption Perception Index' (S&P, 2013). Despite the differences between CI and CCI, the significance of the proxy CCI highlights the relevance of the government transparency as a driver of split bank ratings between S&P and Moody's, confirming that corruption increases bank-risk taking behaviour (see Chen et al., 2015).

Table 5.8 also shows that the coefficient for *Ownership* is significant (at the 5% level) in both Models I and II. The unexpected negative sign of the coefficient may suggest differences in the opinion regarding the type of ownership. For instance, Bowe and Larik (2014) find that institutional ownership improves corporate governance, reducing the probability of split ratings between Moody's and S&P in corporate firms. Thus, they suggest that private ownership reduces rating divergences. Moreover, Williams et al. (2015) indicate that during periods of financial distress the government's capability to offer support decreases, hence, some GRAs may perceive private banks as more capable to stand crisis' periods, which would decrease the probability of observing split ratings. In Table 5.8, *Invrating* is also highly significant and the coefficient has the expected negative sign. An investment grade rating decreases the probability of future split ratings by 0.18% (in Models I and II), showing the relevance of incorporating the speculative-investment rating threshold as a driver of split bank ratings.

The coefficient of *Sovereign* is significant in Model II and has an unexpected positive sign, suggesting that the probability of split bank ratings in countries with sovereign rating level which is one-notch higher than the average sovereign rating[114] increases by 1.48% compared to countries with weaker sovereign ratings. Since the variable *Sovereign* is constructed as the average of S&P, Moody's and Fitch sovereign ratings, the results may show differences in the sovereign risk perception. Fitch could assign higher sovereign ratings than S&P and Moody's, and S&P assigning the lowest sovereign rating, which would increase the likelihood of S&P assigning lower bank ratings than Moody's, if the sovereign risk is transferred to bank ratings. The results would be in line with Williams et al. (2013), who show that the rating channel of transmission from sovereign risk to bank ratings is strong in emerging economies. Moreover, Vu et al. (2017) show that S&P is usually more conservative in sovereign ratings when

[114] The average sovereign rating for the sampled banks is 10 (i.e. BBB/Baa2 for S&P, Fitch/Moody's) based on the 18-point numerical scale.

compared to Moody's and Fitch. Further discussion on the effect of split sovereign ratings on bank ratings is presented in Chapter 6, Section 6.2.

Table 5.9 presents the results for S&P and Fitch. *Size* is the only financial variable that has a statistically significant coefficient and has the expected positive sign in both Models I and II. The likelihood of split ratings increases by 2.50% (in both Models I and II), for a *Size* comparison between US 40,104 million to US$47,778 million.[115] Considering that more than half of the observations in the sample are with split ratings, the probability is economically significant. The results show that the complexity of the bank business increases the uncertainty surrounding banks' creditworthiness, confirming the findings in Morgan (2002) and Iannotta (2006). As expected, the development of the financial sector decreases rating disagreements between S&P and Fitch (in Table 5.9). An increase of 1% in the ratio *Domestcredit* decreases the probability of split bank ratings by 3.16% in Model I (3.26% in Model II), indicating that uncertainty in the bank credit risk diminishes in countries where the financial system is more developed, consistent with the findings of Williams et al. (2015). The likelihood of having split ratings increases by 0.29% (Model I) if the bank has private *Ownership* compared to public ownership (Model II reports similar results). This result contributes to a debate in the literature, implying that GRAs perceive higher government support when assigning ratings of state-owned banks, but is aligned with the findings of Correa et al. (2014). The proxies of *Corruption* are not significant in explaining S&P and Fitch split ratings.

Table 5.10 presents the results for banks rated by Moody's and Fitch. Bank *Size* is not a significant determinant of the split ratings between those GRAs. Instead, *Profitability* and *Liquidity* are highly significant (at the 1% level) in Models I and II and both coefficients have the expected negative sign. In Model I, an increase of 1% in *Profitability* or *Liquidity* decreases the probability of split ratings by 0.22% (similar results are observed in Model II). This result shows that rather than the complexity of the bank business, for Moody's and Fitch's higher liquidity and profitability generate less uncertainty in their rating opinions, confirming the findings in prior literature (see Morgan, 2002; Bissoondoyal-Bheenick and Treepongkaruna, 2011; Bowe and Larik, 2014). Furthermore, contrary to the S&P and Fitch pair, a more developed financial sector increases split ratings between Moody's and Fitch, which is a relevant finding that contrast with prior research. This result could be associated with the weighting of risk factors in the rating methodology of each GRA or the rating conservativeness

[115] This represents an increase of 1% in the natural log of *Size* at its mean.

of one of the GRAs (the latter aspect is discussed in Section 5.6.2). As expected, if the bank is rated at investment grade, the probability of split ratings decreases (by 0.13% in this case).

5.6.2 Influence of opacity on the lopsided behaviour of the GRAs

The conservative behaviour of one GRA when split ratings occur is called "lopsided effect" by the literature (Morgan, 2002; Livingston et al., 2007). The preliminary evidence presented in Section 5.4.1 shows that in the sampled banks, S&P is the most conservative GRA when split ratings occur; S&P assigns a lower rating in 80% (78%) of the observations when compared to Moody's (Fitch) (see Table 5.1 Panel B). Vu et al. (2017) report the same lopsided behaviour in S&P when rating European and non-European sovereigns. Overall, the tests of Hypothesis IB show that split bank ratings are lopsided and that the banks' opacity increases the probability of lopsided ratings of one of the GRAs.

Tables 5.11 to 5.13 present the results of Eq. (5.2) and Eq. (5.3) for each pair of GRAs. The expected signs for the inferior ratings are the same as in Eq. (5.1). *Hypothesis IB* tests whether the split bank ratings tend to be lopsided, with one GRA tending to assign lower ratings than the other. Therefore, the results discussed here correspond to the estimations where GRA1 assigns an inferior rating than GRA2, for each pair of GRAs.

Table 5.11 reports the estimations of the drivers of split bank ratings between S&P and Moody's, when S&P assigns superior and inferior ratings than Moody's. *Size* and *Capital* are statistically significant in Model I, while *Size, Capital* and *Profitability* are statistically significant in Model II. In both models, the coefficients have the expected sign. The marginal effects (or economic significance) of *Size* is stronger than for the other two financial variables in Model II. The likelihood of receiving a lower rating by S&P versus Moody's rises by 3.90% in Model I (4.31% in Model II), for a bank *Size* comparison between US$38,796 million (average size) to US$ 46,205 million. Moreover, a 1% increase in *Capital* increases the probability of S&P assigning an inferior rating by 0.18% in Model I (0.22% in Model II), while the same increase in *Profitability* decreases the probability of S&P assigning a lower rating than Moody's by 0.08%. The results are consistent with the findings of previous literature on the effect of bank size and capital, suggesting that business complexity and capital levels are important sources of bank rating disagreements (see Section 5.4.2).

The coefficients of *Domestcredit, Ownership, Sovereign,* and *Invrating* in Table 5.11 are strongly significant in both Models I and II. Amongst them, *Sovereign* has the strongest economic significance. The unexpected positive sign may have a similar explanation as for Table 5.8. The variable *Sovereign* is defined as the average of S&P, Moody's and Fitch sovereign ratings. Therefore, different perceptions of the sovereign risk, with S&P being the most conservative GRA (typically assigning the lowest sovereign rating) among the three GRAs, would increase the likelihood of S&P assigning lower bank ratings than Moody's. The results would be in line with the literature that shows that there is a rating channel of transmission of sovereign risk to bank ratings (see Shen et al., 2012; Williams et al., 2013). The significance of both proxies of government transparency shows that the country's level of corruption is relevant in explaining the tendency of assigning lower ratings by S&P. This supports the findings of Chen et al. (2015), that banks' risk-taking behaviour is stronger in countries with higher corruption. The marginal effects show that if *CCI* (*CI*) increases by 1%, the likelihood of S&P assigning a lower rating rises by 0.63% (4.95%).

Table 5.12 presents the estimations of the drivers of split bank ratings between S&P and Fitch, when S&P assigns superior or inferior ratings than Fitch. The results show that S&P inferior ratings are highly influenced by the bank *Size*, while the other financial variables are not statistically significant. The likelihood of receiving a lower rating by S&P increases by 5.04% in Models I (5.01% in Model II), for a bank *Size* comparison between US$40,104 million (average size) and US$47,778 million. The relevance of *Size* suggests that larger banks generate more uncertainty among the GRAs, supporting the findings by Iannotta (2006) for European banks. The control variable with strong statistical significance is *Domestcredit,* which has the expected negative sign. The probability of S&P being more conservative than Fitch decreases by 1.94% in Model I (2.13% in Model II) when the banking sector has more depth and development. Unlike Table 5.11, the coefficient of *Ownership* has positive sign, suggesting that ownership is a relevant variable to compare the effects of rating competition amongst GRAs, since the weight and risk assessment of the variable in the rating methodology of S&P should be the same, regardless of whether the bank is rated also by Moody's or Fitch. Regarding the proxies of government transparency, only the coefficient of *CI* is significant (at the 10% level) in Model II, however, it has an unexpected negative sign. An increase of 1% in *CI* decreases by 2.11% the probability of receiving a lower rating by S&P, suggesting that Fitch is more conservative in the ratings than S&P when the government is less transparent. Prior literature finds that Fitch sovereign ratings tend to be more sensitive to political risk issues than S&P or Moody's (see Vu et al., 2017). Accordingly, the results may show that Fitch bank ratings are highly influenced by the sovereign rating assignments in countries with greater corruption problems.

Table 5.13 presents the results for split ratings between Moody's and Fitch, using Moody's superior and inferior ratings as dependent variable. When Moody's assign inferior ratings, *Capital* and *Profitability* have statistically significant coefficients, particularly the former ~~latter~~ variable. An increase of 1% in the *Capital* ratio increases the probability of Moody's assigning a lower rating by 0.73% (in Models I and II). The same percentage increase in *Profitability* decreases the probability of Moody's assigning a lower rating by 0.44% (in Models I and II). These results contribute to the literature by showing that the banks' leverage is a source of rating disagreements between GRAs. It also shows that profitability is not only an important driver of split corporate ratings but also it is relevant when discussing split ratings in the banking industry. Regarding the control variables, the marginal effects show that Moody's inferior ratings are more sensitive to *Domestcredit* than to *Ownership*. Moody's has a lower likelihood of assigning an inferior rating when the banking sector is more developed, while there is a greater probability of inferior Moody's bank ratings than Fitch in a private-owned bank compared to a state-owned bank. Jiang and Packer (2017) show that state-owned Chinese banks are perceived by the GRAs as less risky than private banks due to the higher likelihood of government support. Thus, the current findings extend Jiang and Packer's (2017) findings to much a broader set of emerging economies.

5.6.3 Effect of bank rating disagreements on the future bank rating changes

Tables 5.14 to 5.16 present the results of the estimations of Eq. (5.4) and Eq. (5.5), which examines the effect of split bank ratings between the two GRAs on the probability of rating changes of one of these GRAs. Overall, the results support the alternative hypothesis by showing that GRAs' future bank rating changes have strong sensitivity to split bank ratings. Nonetheless, the response of each GRA's rating migration to the split ratings is different. The results suggest that S&P has a strong reputation in emerging economies because the other two GRAs seem to be more sensitive to S&P ratings than vice versa. The estimation results also imply that competition between GRAs is a relevant factor when assigning ratings in emerging economies.

Table 5.14 reports the results for banks rated by S&P and Moody's. A more-than-one-notch higher Moody's rating increases the probability of S&P's future rating upgrades by 5.01% but does not affect S&P rating downgrades. Inferior Moody's ratings do not have any effect on S&P's future ratings. In contrast, S&P superior and inferior ratings have a statistically significant impact on Moody's future rating migrations. A bank with more-than-one-notch higher rating by S&P has a greater (lower) probability of being upgraded (downgraded) by Moody's in the following quarter by 7.15% and 1.97%, respectively. If S&P has one-notch and more-than-one-notch inferior rating, the likelihood of an upgrade by Moody's decreases by 2.61% and 1.64%, respectively. A more-than-one-notch inferior S&P rating increases the banks' likelihood of being downgraded by Moody's by 8.75%.

The results in Table 5.14 indicate that Moody's rating migrations are highly sensitive to S&P ratings in the presence of a split, compared to S&P future rating changes, which only show responsiveness to Moody's superior ratings. Considering that Moody's is more inclined to modify the rating before the next annual review after a split, it is unlikely that Moody's rating changes occur as a result of new information released by the rated bank. However, Moody's rating migrations could be the result of reputational effects from S&P and/or the high bank opacity in emerging economies. Since S&P tends to assign lower ratings (80% of the sampled observations have inferior ratings assigned by S&P), Moody's could be interpreting S&P's lower ratings as an information signal that it is overrating the bank (even if the bank's risk profile has not changed), which would explain the downgrades. Moreover, any concerns of Moody's rating competitively if S&P assigns superior ratings would lead to rating upgrades in the next quarter. Therefore, the results are consistent with S&P's high reputational capital and herding behaviour from Moody's found by Lugo et al. (2015).

Table 5.15 considers banks rated by S&P and Fitch. When Fitch assigns more-than-one-notch superior ratings, the probability of S&P upgrading the bank increases by 11.8%, while more-than-one-notch superior rating by S&P increases the likelihood of future Fitch upgrades by 20.6%. Moreover, when Fitch (S&P) ratings are one-notch lower than S&P (Fitch), the probability of S&P (Fitch) future downgrades increases by 4.50% (1.77%). These results show that S&P and Fitch tend to influence each other's rating changes, consistent with the findings of Alsakka and ap Gwilym (2010b). However, the marginal effects show different sensitivities between S&P and Fitch, suggesting that the reputation effects and competition between these GRAs influence their rating responses. When split ratings occur and Fitch assigns the lower rating, the bank is more likely to be downgraded by S&P in the next quarter. This suggests

S&P has reputational concerns as the most conservative GRA,[116] which leads to rating convergence. The result contrasts with some findings from the prior literature, which show that Fitch (Lugo et al., 2015) and Moody's (Güttler, 2011), tend to converge to S&P ratings.[117] Regarding future rating upgrades, the high sensitivity of Fitch to S&P superior ratings may suggest a competition effect, where Fitch, pressured by the high rating assigned by the competitor, upgrades the bank rating. This behaviour would be supporting the evidence in Park and Lee (2018).

Table 5.16 considers the influence of Fitch and Moody's superior/ inferior ratings on the probability of future rating changes of both GRAs. The probability of a future Moody's rating upgrades increases by 1.96% when Fitch has more-than-one-notch superior ratings. However, superior Fitch ratings do not have any impact on the probability of future Moody's downgrades. In contrast, Fitch conservativeness has a significant effect on the likelihood of Moody's future rating changes. The probability of a future upgrade by Moody's decreases by 2.28% and 1.51%, when Fitch assigns one-notch and more-than-one-notch inferior ratings, respectively. A more-than-one-notch inferior Fitch rating leads to a higher likelihood of Moody's downgrades by 8.11%. In comparison, if Moody's rates higher than Fitch, Moody's does not influence the behaviour of Fitch ratings. Moody's inferior rating (one-notch) increase the probability of Fitch future downgrades by 1.68%, while if Moody's assigns a more-than-one-notch inferior rating, it is 1.89% less likely that the bank receives a future upgrade by Fitch. Note that the impact of Moody's conservative behaviour on Fitch is statistically significant only at the 10% level. Therefore, Moody's future rating changes are highly sensitive to Fitch ratings when split ratings occur, particularly when Fitch assigns inferior ratings. In contrast, Fitch rating migrations are not influenced by Moody's ratings. The high probability of rating convergence, after assigning lower ratings by Fitch than Moody's and the higher percentage of split rating observations with lower Fitch ratings (57.8%), implies that Moody's adjusts its ratings to match a more conservative competitor, in this case, Fitch. This finding supports the herding behaviour among the GRAs suggested by Lugo et al. (2015).

In summary, S&P superior and inferior ratings greatly affect future rating changes by Moody's, while only harsh split ratings (more-than-one-notch) by S&P affect Fitch rating changes. Fitch

---

[116] 78% of the split rating observations between S&P and Fitch have S&P lower bank ratings, which suggests that S&P tends be much more conservative than Fitch when assigning bank ratings in the sampled countries.

[117] Güttler (2011) finds that S&P tend to lead rating changes and Moody's ratings tend to converge to S&P ratings (please see Section 3.2.3).

rating disagreements with S&P (Moody's) have a significant effect on future rating changes by S&P (Moody's), showing a stronger impact on S&P rating upgrades than on Moody's rating downgrades. Only Moody's superior ratings are influential on S&P upgrades while the effect on Fitch future rating changes is weaker, suggesting that among all three GRAs, Moody's is the less influential GRA. Although the probability of future rating changes is below 10.0% on average, the percentage of rating upgrades and downgrades for all pairs of GRAs is less than 9.0% of the total number of observations (see Table 5.3), showing how meaningful are the probabilities estimated in the models. Nonetheless, the low percentage of rating changes during the period of analysis shows the high stability of bank ratings assigned by the three GRAs in the sampled emerging economies. Considering that split ratings' observations represent more than 50% of the total sample, the low percentage of rating changes suggests that split bank ratings in emerging economies tend to remain split. This is a novel finding, as rating persistence has only being examined for split corporate ratings by Livingston et al. (2008) and by Bowe and Larik (2014).

It is also relevant to highlight the leading behaviour of S&P ratings compared to Moody's and Fitch ratings, considering that 86.3% (82.5%) of the observations with split ratings have a lower S&P rating compared to Moody's (Fitch), and split ratings observations represent 76.1% (56.5%) of the total observations of the two pair of GRAs. However, superior Fitch ratings also affect S&P future rating upgrades. Also, 58.7% of Moody's and Fitch split ratings observations have inferior Fitch ratings, which is relevant considering that Fitch inferior ratings have a significant effect on the probabilities of Moody's future rating upgrades, while Moody's split ratings do not have an effect on Fitch future rating changes.

The pseudo-R^2 values of the estimations confirm the findings. When estimating the effect of S&P superior/inferior rating on Moody's upgrades (downgrades), the pseudo-R^2 value is 21.1% (17.8%), compared to 16.6% (15.0%) when analysing the impact of Moody's superior/inferior ratings on S&P rating changes, implying the strong influence of S&P behaviour. When estimating the effect of S&P superior/inferior ratings on Fitch upgrades (downgrades), the pseudo-R^2 value is 13.5% (19.2%), while the pseudo-R^2 value in the estimations of the effect of Fitch superior/inferior rating on S&P upgrades (downgrades) is 17.5% (16.6%), suggesting that both GRAs influence each other rating decisions.

5.6.4 Robustness tests

5.6.4.1 The determinants of split ratings using an ordered probit model

Section 5.6.1 consider split ratings between each pair of GRA using a binary probit model approach. As a robustness test, the rating differences in notches are considered. In the samples, the most common case is one-notch split ratings, nevertheless, on average, 23.0% of the observations have split ratings of more than one-notch. To consider the discrete, ordinal nature of rating disagreements, Eq. (5.1) is estimated using an ordered probit model. The specification of the model is as follows:

$$OrdSplit^{*}_{i,j,t} = \alpha_n \sum_{n=1}^{4} X_{i,n,t-1} + \beta_k \sum_{k=1}^{4} Controls_{i,k,t} + \delta YD + \theta CD + \varepsilon_{ijt} \tag{5.6}$$

$OrdSplit^{*}_{i,j,t}$ is an unobserved latent variable linked to the observed ordinal response categories $OrdSplit_{i,j,t}$ by the measurement model:

$$OrdSplit_{i,j,t} = \begin{cases} 0\ (i.e. non-split\ ratings) & ,\ if\ OrdSplit^{*}_{i,j,t} \leq \mu_1 \\ 1\ (i.e. split\ ratings\ by\ one\ notch) & ,\ if\ \mu_1 < OrdSplit^{*}_{i,j,t} \leq \mu_2 \\ 2\ (i.e. split\ ratings\ by\ two\ notches) & ,\ if\ \mu_2 < OrdSplit^{*}_{i,j,t} \leq \mu_3 \\ 3\ (i.e.\ split\ ratings\ by\ three\ or\ more\ notches) & ,\ if\ \mu_3 < OrdSplit^{*}_{i,j,t} \end{cases}$$

Where μ_m denote thresholds, subject to the constraint that $\mu_1 < \mu_2 < \mu_3$. $OrdSplit_{i,j,t}$ corresponds to the absolute value of the quarterly rating differences of each pair of GRAs of bank *i* in country *j*. The subscripts i, j, t denote bank, country, and time (quarterly), respectively. The explanatory variables and the controls are the same as in Eq. (5.1).

Tables A. 5.1 to A 5.3 in the Appendix presents the estimations of Eq. (5.6). The results are consistent with the results of Eq. (5.1). As in the binary models, the financial variables employed as a proxy of bank opacity have an effect on the probability of split ratings, although their statistical significance differs from the main estimations. The economic effects are stronger for two-notch split ratings, showing that higher rating differences reflect higher bank opacity. Nevertheless, the economic effect disappears in more-than-two-notches split ratings, which is explained by the lower number of split ratings at this category (see Table 5.1).

With some exceptions, the variables which are significant in the binary model remain significant in the ordered probit model. The economic effect of the financial and the macroeconomic variables is stronger on a one-notch split, except for S&P and Fitch for which the marginal effects are stronger for two-notch split ratings. As in the binary estimation, *Size* has the strongest effect on the probability of split ratings between S&P and Moody's. The marginal effect of *Profitability* is greater than the marginal effects of the other financial ratios for S&P and Fitch, and Moody's and Fitch, suggesting that the variable is one of the main drivers of split ratings between these two pairs of GRAs. Regarding the control variables, for S&P and Moody's, the coefficient of *Invrating* has the highest statistical significance, particularly for two-notch split ratings. For S&P and Fitch, *Ownership* has a highly significant impact on the probability of split ratings. For Moody's and Fitch, the level of development of the financial system represented by *Domestcredit* has the strongest impact on the probability of split ratings.

5.6.4.2 Rating migrations using an ordered probit model

Table 5.3 shows that the most common rating change in all three pairs of GRAs is one-notch upgrade or downgrade. Nevertheless, on average, 13.5% of the observations are rating changes of more than one-notch, and rating changes by Moody's of more than one-notch (particularly downgrades) are more common than in S&P or Fitch. Therefore, to capture the effect of split ratings on the quarterly rating changes in notches, as robustness test, Eqs. (5.4) and (5.5) are estimated using an ordered probit model approach. $OrdUpgGRA^{*}_{i,j,t}$ ($OrdDwnGRA^{*}_{i,j,t}$) are unobserved latent variable related to the observed ordinal rating changes *OrdUpgGRA* (*OrdDwnGRA*) that take the value of 1, 2, or 3, representing upgrades (downgrades) of bank *i* from country *j* in quarter *t* by 1,2 or 3 or more notches, respectively; 0 if the rating has not changed. The explanatory variables are the same as in Eqs. (5.4) and (5.5).

Tables A 5.4 to A 5.6 in the Appendix present the estimations of the ordered probit model for each pair of GRAs. Overall, the results are consistent with the evidence from Eq. (5.4) and Eq. (5.5). The magnitude of the split influences GRAs' future rating changes and the effect of split ratings is stronger on upgrades than downgrades. Future upgrades (downgrades) from GRA1 are more responsive to split ratings when GRA2 assigns a two-notches superior (inferior) rating. The analysis of MEs shows that when the bank has split ratings, and one of the GRAs assign a superior rating (of one or more notches), the other GRA is more likely to change the rating by one-notch during the next quarter. However, the MEs show that it is not likely that split ratings induce rating changes of more-than-one-notch. For instance, if Moody's assigns a more-than-one-notch superior rating, then the probability of S&P upgrades by one-notch in the next quarter increases by 4.5%, while the likelihood of future rating changes of more-than-one-notch by S&P raises only by 0.48% (See Tables A. 5.4 of Appendix 5). The strongest effects between those two GRAs occur in split ratings where S&P assigns a more-than-one-notch inferior rating. In that case, the split raises the likelihood of a one-notch (more-than-one-notch) future downgrade by Moody's by 6.99% (2.02%). The results suggest that Moody's rating migrations are more influenced by the conservativeness of S&P, than the other way around.

The strongest reaction of future rating changes to split ratings occurs between S&P and Fitch (see Table A 5.5 in the Appendix). When S&P (Fitch) assigns a more-than-one-notch higher rating than Fitch (S&P), the probability of Fitch (S&P) upgrading the rating in the next quarter raises by 19.42% (9.69%), suggesting a strong interdependency between those two GRAs. The effect of the conservativeness of those two GRAs when split ratings occur is less significant in downgrades.

Table A 5.6 in the Appendix shows that when split ratings occur, Fitch ratings have a high influence on Moody's future rating changes, while Moody's ratings have no significant effect on Fitch's future rating changes. When Fitch has a more-than-two-notches inferior rating, the probability of Moody's downgrading the bank rating by one-notch in the next quarter raises by 5.77%.

5.6.4.3 The case of split bank ratings across the three GRAs

Previous literature shows that a third rating can solve split ratings or act as a "tie-breaker" (Baker and Mansi, 2002; Bongaerts et al., 2012), and even affect the issuer's cost of issuance (Mählmann, 2009). Moreover, when a corporate is rated by all three GRAs, the third rating influences the GRAs' rating changes (Becker and Milbourn, 2011; Bowe and Larik, 2014). Vu et al. (2015) find that sovereign bond spreads are more sensitive to negative rating events by S&P, when S&P assigns a rating lower than both Moody's and Fitch. After trimming and matching with the financial data, the sample comprises 60 banks rated by all three GRAs (701 observations), and 26.2% of the observations (184/701) have split ratings by any of the GRAs versus the other GRAs. To incorporate the findings from the literature, two robustness tests are included. Firstly, the influence of opacity on the probability of split ratings across all three GRAs is examined by using the binary probit modelling approach - Eq. (5.1). In this case, the dependent variable $SplitGRAs$ is a dummy variable that takes the value of one when the bank has split ratings by any pair of GRAs, zero otherwise. This split ratings' case has the same explanatory variables and controls as in Eq. (5.1). Model (I) includes CCI and Model (II) includes CI.

Table A 5.7 in the Appendix presents the estimation of the robustness test. The results are consistent with previous findings, suggesting that opacity is a relevant determinant of the split bank ratings across all three GRAs. Amongst the financial variables, *Capital* and, to a less extent, *Liquidity*, are both statistically and economically significant variables affecting the probability of having split ratings by any of the GRA versus the other GRAs. Model II shows that an increase of 1% in *Capital*, increases the probability of split ratings across the three GRAs by 1.21%, while the same increase in *Liquidity* ratio reduces the likelihood of split ratings by 0.22%. Amongst the control variables, the coefficient of *Sovereign* has the strongest impact. Higher sovereign rating level would decrease the probability of split ratings by any of the GRAs versus the other two GRAs by 11.72%.

The second robustness test evaluates if banks with split ratings by any of the GRAs versus the other two GRAs are more susceptible to show future rating changes than non-split banks rated by all three GRAs. This investigation is based on Eq. (5.4) and Eq. (5.5), and is as follows:

$$UpgGRA^{*A}_{i,j,t} = \beta_1 SupGRA^{ABC}_{i,j,t-1} + \beta_2 InfGRA^{ABC}_{i,j,t-1} + \gamma_h \sum_{h=1}^{18} Rating_{i,h,t-1} + \delta YD + \theta CD + \varepsilon_{ijt} \quad (5.7)$$

$UpgGRA^{*A}_{i,j,t}$ is an unobserved latent variable that is linked to the observed response variable $UpgGRA^{A}_{i,j,t}$by the measurement model:

$$UpgGRA^{A}_{i,j,t} = 1 \; if \; UpgGRA^{*A}_{i,j,t} > 0$$

$$UpgGRA^{A}_{i,j,t} = 0 \; if \; UpgGRA^{*A}_{i,j,t} \leq 0$$

For downgrades, the model specification is as follows:

$$DwnGRA^{*A}_{i,j,t} = \beta_1 SupGRA^{ABC}_{i,j,t-1} + \beta_2 InfGRA^{ABC}_{i,j,t-1} + \; \gamma_h \sum_{h=1}^{18} Rating_{i,h,t-1} + \delta YD + \theta CD + \varepsilon_{ijt} \quad (5.8)$$

$DownGRA^{*A}_{i,j,t}$ is an unobserved latent variable that is linked to the observed response variable $DownGRA^{A}_{i,j,t}$by the measurement model:

$$DownGRA^{A}_{i,j,t} = 1 \; if \; DownGRA^{*A}_{i,j,t} > 0$$

$$DownGRA^{A}_{i,j,t} = 0 \; if \; DownGRA^{*A}_{i,j,t} \leq 0$$

The subscripts i, j, t denote bank, country and time (quarters), respectively. The binary variable $UpgGRA^{A}_{i,j,t}$ ($DownGRA^{A}_{i,j,t}$) takes the value of one if any GRA (S&P, Moody's or Fitch) upgrades (downgrades) the bank one or more notches, zero if the rating assigned by any GRA does not change.

The explanatory variables follow the definition of "triple - rating" by Vu et al. (2015), $SupGRA_{i,j,t-1}^{ABC}$ is a dummy variable defined as one if GRA^{ABC} (any of the three GRAs) assigns a superior rating compared to at least one of the remaining GRAs. $InfGRA_{i,j,t-1}^{ABC}$ is a dummy variable defined as one if GRA^{ABC} assigns an inferior rating compared to at least one of the remaining GRAs.

Table A 5.8 in the Appendix presents the estimations of Eqs. (5.7) and (5.8). The results support the evidence found in Eq. (5.4) and (5.5). Rating migrations are affected by split ratings between GRAs. Similar to the case of split ratings between two-pair of CRAs, if S&P assigns a superior rating compared to Moody's and/or Fitch, it induces a strong reaction on Fitch future actions, increasing the probability of an upgrade by Fitch by 6.89%, but it does not have any effect on Moody's rating migrations in the future. Inferior S&P ratings versus Fitch and/or Moody's decreases the probability of Moody's upgrades by 3.52% but has no effect on Fitch future rating changes. Moody's superior ratings have no significant influence on future rating changes of S&P or Fitch, while an inferior rating by Moody's decreases the probability of future Fitch's rating upgrades by 1.82%. Fitch superior ratings versus S&P and/or Moody's decreases the likelihood of Moody's future downgrades by 3.52%, while it does not have any significant effect on S&P rating migrations. When Fitch assigns an inferior rating compared to S&P and/or Moody's, the probability of S&P upgrades decreases by 2.35%, while it does not have an impact on Moody's upgrades.

5.7 Conclusions

This Chapter examines the determinants of split bank ratings between GRAs in the emerging markets. The Chapter also investigates the influence of split bank ratings between GRAs on their future rating changes. A sample of 78 banks rated by S&P and Moody's (862 observations), from 9 countries; 76 banks (798 observations) from 10 countries rated by S&P and Fitch; 64 banks (813 observations) from 9 countries rated by Moody's and Fitch, during October 2008 to December 2015 is employed. To understand the role of opacity in split bank ratings and rating migrations, the Chapter investigates the drivers of split bank ratings using a binary probit model, which is a common approach in the literature of split ratings (e.g. Morgan, 2002; Bowe and Larik, 2014). Moreover, the estimation of marginal effects allows measurement of the economic effect of the opacity proxies on the split ratings. An improved understanding of the effects of harsher split ratings upon future rating changes evolves from this.

Among all economic sectors, the literature shows that the banking industry is the most opaque (Morgan, 2002; Flannery et al., 2004; Fosu et al., 2017, 2018). Previous research shows that split ratings are an accurate proxy of the level of opacity in an industry (e.g. Morgan, 2002; Iannotta, 2006; Livingston et al., 2007). These studies, however, are conducted in developed economies, where the government has high levels of transparency and there exists a strong institutional framework. Thus, the study of the impact of opacity on split bank ratings should be much more relevant in emerging economies, where these conditions are typically not observed to the same extent. The descriptive analysis of the data supports this argument, showing that 76.1% of the observations have split ratings between S&P and Moody's, 56.5% between S&P and Fitch and 66.4% between Moody's and Fitch, which contrasts with prior studies where the percentage is below 50%.[118] Secondly, as public information in emerging economies has relatively lower quality, changes in issuers' creditworthiness may not be perceived by market participants. The Chapter reveals that GRAs' split ratings convey relevant information about the GRAs' future rating changes, consistent with some prior literature (e.g. Livingston et al., 2008; Alsakka and ap Gwilym, 2010c). Consequently, split ratings, and

[118] Iannotta (2006) shows that S&P and Moody's disagree in 36.7% of the cases (between 1993 and 2003). Livingston and Zhou (2016) show that 47.4% of the sample of European corporates have split ratings between those two GRAs (during the period 2000 - 2014).

especially the magnitude of those splits (in notches), can also indicate a potential for deterioration of the issuers' credit quality, which is valuable information in these economies.

The findings of the Chapter confirm the opacity hypothesis as an explanation for split bank ratings, consistent with Morgan (2002) and Livingston et al. (2007). The estimations reveal that financial variables, which are used as a proxy of asset opacity, have a significant effect on the probability of rating disagreements between GRAs. Larger bank *Size*, higher *Capital*, lower *Profitability* and lower *Liquidity* increase the probability of split ratings. However, the opacity proxies have a different effect on split ratings depending on the pair of GRAs. *Size* has a strong impact on split ratings between S&P and the other two GRAs, while *Liquidity* and *Profitability* have stronger effects on the probability of split ratings between Fitch and Moody's. When using an ordered probit model estimation, the results reveal that the economic significance of the opacity proxies increases with the magnitude of the split ratings (notch-differential).

The Chapter also investigates if split bank ratings in emerging economies are lopsided, following Morgan (2002) and Livingston et al. (2007). Namely, if one of the GRAs systematically assigns lower ratings than the other GRAs. Preliminary evidence from the data analysis reveals that S&P assigns inferior ratings in more than 80% (78%) of the split ratings observations compared to Moody's (Fitch). Although the results confirm that S&P tends to be more conservative in bank ratings than the other GRAs, they contrast with evidence of split ratings in US banks and European corporates, whereby Moody's is more conservative than S&P (see Morgan, 2002; Livingston et al., 2010). The multivariate analysis shows that opacity has a strong effect on the rating conservativeness. Larger bank *Size* increases the probability of S&P assigning lower bank ratings than Moody's or Fitch, while higher *Profitability* decreases the likelihood of Moody's assigning lower bank ratings than Fitch.

The results also show that rating disagreements have a significant effect on the likelihood of subsequent rating changes. The influence of split ratings is greater on rating upgrades than downgrades. The higher the split differential (in notches), the stronger the effect on the probability of a rating change, especially for rating upgrades. Consistent with Alsakka and ap Gwilym (2010b), the study shows evidence of interdependence between the three GRAs. The likelihood of an upgrade (downgrade) by one of the GRAs is higher for banks with previous superior (inferior) ratings by any other GRA. The strongest interdependence is observed between Fitch and S&P, while Moody's rating behaviour when split ratings occur has the weakest influence on S&P or Fitch future rating migrations. The estimations also suggest that S&P rating changes are the least dependent on the rating changes by the other two, although rating divergences with Fitch seems to influence S&P rating migrations. Since wider rating differential (in notches) is associated with higher bank opacity, this implies that asset opacity has a relevant role in explaining bank rating migrations in emerging economies. The significant effect of opacity on future rating changes is consistent with the findings on sovereign split ratings in emerging economies by Alsakka and ap Gwilym (2010c).

Given the more limited availability of financial information from banks in emerging economies, the Chapter provides important insights. For policy makers, the high bank opacity demonstrates the importance of undertaking measures to improve the transparency and quality of the information in the banking industry and to reduce bank risk appetite, especially in larger banks, as the results show they tend to have higher opacity. The role of bank opacity in the significant proportion of split ratings of total observations also shows for regulators and academics the relevance of evaluating how effective is the market discipline in the banking sector, as opacity weakens the market discipline and motivates banks to engage in riskier activities and hence, have more probability of facing higher funding costs (Fosu et al., 2017). Moreover, the significant effect of split ratings on future rating changes is relevant for studies on transition matrices of GRAs. Thus, for issuers with multiple ratings by GRAs, these matrices should not only incorporate the evolution of the issuers' own ratings but also the evolution of rating disagreements, which is proposed for corporates by Livingston et al. (2008). From the results, the evolution of split ratings of the past three to four years could be a relevant tool for projecting possible scenarios of future rating changes, which can be incorporated in the investors' decision-making process. Additionally, the interdependencies of rating disagreements between GRAs and their future rating changes, and the significant effect of opacity on these rating migrations open the discussion on the need of developing a unified regulation for GRAs operating in emerging economies, as an approach to reduce uncertainty in these countries.

The tendency toward conservativeness displayed by S&P bank ratings in emerging economies should be considered by investors when planning their investments, as an additional source of information on the bank opacity. For investors, knowing which GRA assigns lower ratings could be an advantage in emerging markets, where the public information is scarce and has relatively low quality. For Moody's and Fitch, the tendency of S&P to be conservative is relevant in terms of reputation, as increased leniency when assigning ratings can distort perceptions of the financial risk of an investment. Namely, if investors are aware of which GRA tends to assign higher ratings, they can use those ratings to comply with regulations when investing, without any regulatory sanction. Furthermore, under financial distress conditions, the rating assignments by GRAs that tend to be less conservative in the ratings won't reflect the increase in the default risk, which is particularly negative for non-professional investors, who have more dependency on GRAs' risk assessments.

Because of the positive implications of decreasing bank opacity, the effects of the implementation of the Basel III regulations for split bank ratings in emerging economies would be an interesting topic for future research. Moreover, an investigation that complements this Chapter could address if investors differentiate between the bank ratings assigned by GRAs in emerging economies and if they consider S&P tendency to rating conservativeness when requiring premiums for opacity (see Livingston and Zhou, 2010, 2016).

Chapter 5 Tables

Table 5.1 Summary statistics of split bank ratings

Panel A. *Split and non-split ratings (Sample before matching the bank ratings with financial data)*

Concept	S&P and Moody's	S&P and Fitch	Moody's and Fitch
Countries	9	10	10
Number of banks with split ratings[a]	87	82	107
Number of banks with no split ratings	5	8	4
Number of observations	1,898	1,767	2,423
Number of split ratings observations	1,418	962	1,679
Split bank ratings (as % of total observations)	74.7%	54.4%	69.3%
Number of superior rating from first GRA	273	211	987
Number of inferior rating from first GRA	1,145	751	692
Inferior rating from first GRA (% split ratings observations)	80.7%	78.1%	41.2%
Detail of split bank ratings in notches			
1 notch higher rating from first GRA	203	178	762
> 1 notch higher rating from first GRA	70	33	225
1 notch lower rating from first GRA	879	563	416
> 1 notch lower rating from first GRA	266	188	276
Detail of split ratings of more than one notch			
2 notches higher rating from first GRA	63	23	177
3 or more notches higher rating from first GRA	7	10	48
2 notches lower rating from first GRA	227	167	248
3 or more notches lower rating from first GRA	39	21	28

Panel B. *Split and non-split ratings after matching the bank ratings with financial data*

Concept	S&P and Moody's	S&P and Fitch	Moody's and Fitch
Countries[b]	9	10	9
Total number of banks with split ratings	71	66	62
Total number of banks with no split ratings	7	10	2
Total number of observations	862	798	813
Number of split ratings observations	656	451	540
Number of same rating observations	206	347	273
Split ratings (as % of total observations)	76.1%	56.5%	66.4%
Superior rating from first GRA	90	79	317
Inferior rating from first GRA	566	372	223
Inferior rating from first GRA (% of split ratings observations)	86.3%	82.5%	41.3%
Detail of higher/lower ratings in notches			
1 notch higher rating from first GRA	69	64	259
> 1 notch higher rating from first GRA	21	15	58
1 notch lower rating from first GRA	438	280	159
> 1 notch lower rating from first GRA	128	92	64
Detail higher/lower ratings of more than one notch			
2 notches higher rating from first GRA	19	10	47
3 or more notches higher rating from first GRA	2	5	11
2 notches lower rating from first GRA	116	83	56
3 or more notches lower rating from first GRA	12	9	8

The table reports the descriptive statistics of the data sample for each pair of GRAs during the period October 2008 to December 2015 (2008Q4-2015Q4). S&P, Moody's, and Fitch bank ratings are transformed into numerical ratings based on an 18-point numerical scale. ***a.*** *At least one quarter with split ratings.* ***b****. For Moody's and Fitch, Argentinean banks are excluded because they do not have financial information reported in Bankscope during the period of analysis (2008Q4-2015Q4).*

Table 5.2 Number of observations with split bank ratings between GRAs per country

	Split bank ratings		
Country	S&P and Moody's	S&P and Fitch	Moody's and Fitch
Argentina	N/A	N/A	24 (1.4%)
Brazil	334 (23.6%)	165 (17.1%)	208 (12.4%)
China	133 (9.4%)	88 (9.1%)	174 (10.4%)
Colombia	28 (2.0%)	25 (2.6%)	23 (1.4%)
Indonesia	97 (6.8%)	109 (11.3%)	121 (7.2%)
Kazakhstan	156 (11.0%)	75 (7.8%)	166 (9.9%)
Mexico	190 (13.4%)	168 (17.4%)	207 (12.3%)
Nigeria	N/A	60 (6.2%)	N/A
Russia	287 (20.2%)	161 (16.7%)	518 (30.8%)
Thailand	128 (9.0%)	88 (9.1%)	114 (6.8%)
South Africa	65 (4.6%)	23 (2.4%)	124 (7.4%)
Total	1,418	962	1,679

The table presents the number of quarterly observations with split bank ratings per country, for each pair of GRAs during the period October 2008 to December 2015. The number in parenthesis reports the number of split bank ratings as a percentage of the total split bank ratings.

Table 5.3 Bank rating changes by S&P, Moody's and Fitch

Pair of GRAs	GRA	Upgrades				Downgrades				No. of rating changes	% of the total observations
		Notches			Total	Notches			Total		
		1	2	≥3		1	2	≥3			
S&P – Moody's	S&P	55	6	2	63	76	7	0	83	146	8.08%
	Moody's	45	9	1	55	75	20	2	97	152	8.42%
S&P - Fitch	S&P	50	4	1	55	72	4	0	76	131	7.81%
	Fitch	48	3	1	52	43	1	1	45	97	5.78%
Moody's - Fitch	Moody's	57	13	1	71	99	20	5	124	195	8.43%
	Fitch	65	5	0	70	69	2	3	74	144	6.23%

The table presents the number of rating changes (upgrades and downgrades) of 1, 2 and 3 or more notches by S&P, Moody's and Fitch, estimated for each pair of GRAs, during the period October 2008 to December 2015. The sample consists of quarterly long-term foreign-currency issuer ratings assigned to banks. Rating changes are reported at the notch level based on an 18-point numerical scale.

Table 5.4 Mean differences of financial variables for non-split vs. split ratings observations

	S&P and Moody's			S&P and Fitch			Moody's and Fitch		
Variable	Non-split	Split		Non-split	Split		Non-split	Split	
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Size (Ln)	17.45	17.46	*0.01*	17.35	17.65	*0.30*	17.62	17.71	*0.09*
	(0.1)	(0.1)		(0.1)	(0.1)		(0.1)	(0.1)	
Capital (%)	9.51	10.23	*0.72*	10.57	10.24	*-0.33*	9.80	9.84	*0.04*
	(0.2)	(0.1)		(0.3)	(0.2)		(0.2)	(0.1)	
Profitability (%)	1.07	1.24	*0.18*	1.25	1.38	*0.13*	1.45	1.16	*-0.29****
	(0.1)	(0.0)		(0.1)	(0.0)		(0.1)	(0.1)	
Liquidity (%)	34.09	30.85	*-3.24**	31.64	29.99	*-1.65*	32.90	30.70	*-2.21*
	(1.3)	(0.6)		(0.9)	(0.7)		(1.2)	(0.7)	
Rating	8.94	9.14	*0.19*	8.93	9.27	*0.34*	9.61	9.57	*-0.03*
	(0.2)	(0.1)		(0.1)	(0.1)		(0.1)	(0.1)	
Number of observations	206	656		347	451		273	540	

*The table reports the mean of each of the opacity proxies: Size, capital, profitability and liquidity, for split-rated observations (A) and non-split rated observations (B) after trimming for each pair of GRAs during the period October 2008 to December 2015. S&P, Moody's, and Fitch ratings are transformed to numerical ratings based on an 18-point numerical scale. The variable 'rating' corresponds to the average bank rating for each pair of GRAs. The numbers in parenthesis report the standard deviation of each variable. Mean differences (C) are assessed using a t-test and the Wilcoxon rank-sum test. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively.*

Table 5.5 Variable description and data sources

Variable	Units	Definition	Source
Size	($) LN	Natural Logarithm of book value of total assets	Bankscope
Capital	%	Equity / Total Assets	Bankscope
Profitability	%	Return on Average Assets (ROAA)	Bankscope
Liquidity	%	Liquid Assets / Deposits and short-term funding	Bankscope
DomestCredit	%	Domestic credit provided by financial sector (% of GDP)	World Bank
Ownership	0/1	Dummy variable = 1 if the bank has private ownership; = 0 if the bank is state-owned	Bankscope
Invrating	0/1	Dummy variable = 1 if the bank is rated at investment-grade; = 0 if the bank is rated at speculative-grade	ID-CREM, Fitch, Moody's, CapitalIQ
Sovereign	1 - 18	Average numerical sovereign rating assigned to sovereign *j* by three GRAs based on the 18-point numerical scale	ID-CREM, Fitch, Moody's, CapitalIQ
CCI	Range (-2.5 to +2.5)	Adjusted Control of corruption Index (CCI). Less corrupt to the most corrupt	World Bank, Worldwide Governance Indicators (WGI)
CI	Range (0 to 2)	Adjusted Corruption index (CI). Less corrupt to the most corrupt.	Transparency International

The table presents the definition and data sources of the variables used in the multivariate analysis. The Control of corruption Index (CCI) is rescaled by subtracting the index from zero, to show that higher values indicate more corruption. Corruption index (CI) is also rescaled to show that higher values correspond to higher corruption. CI is deducted by 10 and divided by the mean of the CI annual index for all countries.

Table 5.6 Summary statistics of the variables

Panel A. *Bank sample rated by S&P and Moody's*

Variable	Obs.	Mean	Std. Dev.	Min	P25	Median	P75	Max
Size	577	17.5	1.6	14.6	16.4	17.5	18.2	21.5
Capital	577	10.0	3.5	3.8	7.4	9.7	11.8	27.9
Profitability	577	1.2	1.2	-4.9	0.8	1.3	1.8	6.0
Liquidity	577	31.2	16.7	4.3	18.6	26.7	39.7	87.5
DomesticCredit	577	91.9	46.2	24.4	45.4	95.2	133.4	185.5
Ownership	577	0.8	0.4	0.0	1.0	1.0	1.0	1.0
Rating	577	0.6	0.5	0.0	1.0	1.0	1.0	1.0
Sovereign	577	10.7	1.5	7.0	10.0	10.3	11.0	14.7
CCI	577	0.4	0.4	-0.2	0.2	0.4	0.6	1.1
CI	577	1.1	0.1	0.9	1.1	1.1	1.2	1.3

Panel B. *Bank sample rated by S&P and Fitch*

Variable	Obs.	Mean	Std. Dev.	Min	P25	Median	P75	Max
Size	526	17.5	1.5	13.3	16.5	17.5	18.1	21.5
Capital	526	10.4	4.0	3.4	7.4	9.8	12.1	27.9
Profitability	526	1.4	1.0	-2.7	0.8	1.3	1.9	6.3
Liquidity	526	30.3	16.1	3.1	18.5	25.8	39.4	87.5
DomesticCredit	526	91.3	48.7	18.8	44.4	95.2	140.6	185.5
Ownership	526	0.8	0.4	0.0	1.0	1.0	1.0	1.0
Rating	526	0.7	0.4	0.0	1.0	1.0	1.0	1.0
Sovereign	526	10.6	1.8	5.5	10.0	10.3	11.0	14.7
CCI	526	0.5	0.4	-0.2	0.3	0.4	0.6	1.3
CI	526	1.1	0.1	0.9	1.1	1.1	1.2	1.3

Panel C. *Bank sample rated by Moody's and Fitch*

Variable	Obs.	Mean	Std. Dev.	Min	P25	Median	P75	Max
Size	560	17.7	1.5	14.5	16.6	17.6	18.2	21.5
Capital	560	9.7	3.2	3.1	7.2	9.5	11.7	23.7
Profitability	560	1.3	1.1	-5.3	0.9	1.3	1.8	5.6
Liquidity	560	31.0	17.4	5.9	18.4	25.4	39.3	89.5
DomesticCredit	560	92.9	49.3	24.4	44.4	95.2	141.7	185.5
Ownership	560	0.8	0.4	0.0	1.0	1.0	1.0	1.0
Rating	560	0.6	0.5	0.0	1.0	1.0	1.0	1.0
Sovereign	560	10.7	1.5	6.7	10.0	10.3	11.0	14.7
CCI	560	0.5	0.4	-0.2	0.3	0.4	0.8	1.1
CI	560	1.1	0.1	0.9	1.1	1.1	1.2	1.3

The Table presents the summary statistics of the variables used in the multivariate analysis for each pair of GRA (Panel A: S&P and Moody's, Panel B: S&P and Fitch, Panel C:Fitch and Moody's). The table reports bank-quarterly observations after matching the financial data with the ratings dataset. The financial and control variables are lagged four quarters (t-4). Obs. stands for observations, Std. Dev. corresponds to standard deviation.

Table 5.7 Pairwise correlations

Panel A. *Banks rated by S&P and Moody's*

Variable		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	Size	1									
(2)	Capital	-0.43	1								
(3)	Profitability	0.06	0.26	1							
(4)	Liquidity	-0.26	0.04	-0.03	1						
(5)	DomesticCredit	0.40	-0.40	-0.03	-0.39	1					
(6)	Ownership	-0.22	-0.09	-0.13	0.05	0.10	1				
(7)	Sovereign	0.71	-0.42	-0.08	-0.31	0.44	0.01	1			
(8)	Invrating	0.62	-0.27	-0.01	-0.05	0.36	0.06	0.46	1		
(9)	CCI	0.04	0.20	-0.05	-0.06	-0.52	-0.04	0.11	-0.14	1	
(10)	CI	-0.14	0.31	0.04	0.04	-0.66	0.02	-0.09	-0.21	0.88	1

Panel B. *Banks rated by S&P and Fitch*

Variable		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	Size	1									
(2)	Capital	-0.46	1								
(3)	Profitability	-0.03	0.42	1							
(4)	Liquidity	-0.25	0.03	-0.06	1						
(5)	DomesticCredit	0.45	-0.37	-0.08	-0.38	1					
(6)	Ownership	-0.30	0.09	-0.06	0.04	0.09	1				
(7)	Sovereign	0.64	-0.47	-0.28	-0.22	0.50	-0.11	1			
(8)	Invrating	0.61	-0.33	-0.17	-0.02	0.40	0.01	0.51	1		
(9)	CCI	-0.07	0.24	0.04	-0.08	-0.56	-0.14	-0.18	-0.19	1	
(10)	CI	-0.24	0.32	0.08	0.00	-0.68	-0.04	-0.29	-0.24	0.88	1

Panel C. *Banks rated by Moody's and Fitch*

Variable		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	Size	1									
(2)	Capital	-0.50	1								
(3)	Profitability	0.04	0.30	1							
(4)	Liquidity	-0.15	-0.04	0.02	1						
(5)	DomesticCredit	0.46	-0.40	-0.05	-0.37	1					
(6)	Ownership	-0.34	0.09	-0.19	0.04	0.10	1				
(7)	Sovereign	0.67	-0.42	-0.12	-0.25	0.48	-0.04	1			
(8)	Invrating	0.54	-0.33	-0.08	0.01	0.40	-0.05	0.31	1		
(9)	CCI	-0.21	0.32	-0.01	-0.10	-0.60	-0.11	-0.03	-0.37	1	
(10)	CI	-0.36	0.40	0.05	0.00	-0.71	-0.03	-0.20	-0.37	0.89	1

This Table presents the correlation matrix estimated for the financial and control variables (lagged four quarters) for each pair of GRAs.

Table 5.8 Determinants of split bank ratings by S&P and Moody's

		Dependent variable: *Split*			
Variable	Expected sign	(I)	ME (%)	(II)	ME (%)
Size	+	0.20**	1.20	0.23**	1.32
		(2.13)		(2.41)	
Capital	+/-	0.03*	0.12	0.05**	0.16
		(1.70)		(2.28)	
Profitability	-	-0.07		-0.12**	-0.49
		(-1.24)		(-2.16)	
Liquidity	-	0.00		0.00	
		(0.02)		(0.35)	
Domestcredit	-	0.00		-0.01	
		(0.39)		(-0.56)	
Ownership	+/-	-0.39**	-010	-0.42**	-0.10
		(-2.15)		(-2.24)	
Sovereign	-	0.25		0.42**	1.48
		(1.16)		(2.16)	
Invrating	-	-0.73***	-0.18	-0.75***	0.18
		(-3.07)		(-3.09)	
CCI	+	0.36			
		(0.55)			
CI	+			12.20***	3.26
				(3.79)	
Observations		577		577	
Country FE		Yes		Yes	
Year FE		Yes		Yes	
Pseudo R-squared		10.9%		13.5%	

The table presents the results of the binary probit estimation (Eq. (5.1)) using data from S&P and Moody's. The dependent variable ***Split*** *takes the value of one when the difference between the quarterly bank ratings assigned by S&P and Moody's is non-zero, and zero when the ratings assigned by both GRAs are equal. For definitions of the explanatory and control variables, see Sections 5.4.2 and 5.4.4., respectively. The Model (I) includes CCI as a proxy of corruption and the Model (II) includes CI as a proxy of corruption. Full sets of country and year dummies are included in both models. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. All variables are lagged four quarters (t-4). The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table 5.9 Determinants of split bank ratings by S&P and Fitch

		Dependent variable: *Split*			
Variable	Expected sign	(I)	ME (%)	(II)	ME (%)
Size	+	0.20**	2.50	0.20**	2.47
		(2.22)		(2.21)	
Capital	+/-	0.01		0.01	
		(0.67)		(0.71)	
Profitability	-	0.03		0.03	
		(0.49)		(0.37)	
Liquidity	-	0.01		0.01	
		(1.39)		(1.41)	
Domestcredit	-	-0.05***	-3.16	-0.05***	-3.26
		(-4.55)		(-4.78)	
Ownership	+/-	0.96***	0.29	0.92***	0.28
		(4.15)		(4.21)	
Sovereign	-	-0.23		-0.27	
		(-1.40)		(-1.61)	
Invrating	-	-0.26		-0.25	
		(-1.09)		(-1.05)	
CCI	+	0.67			
		(0.94)			
CI	+			-0.52	
				(-0.21)	
Observations		526		526	
Country FE		No		No	
Year FE		Yes		Yes	
Pseudo R-squared		17.2%		17.1%	

The table presents the results of the binary probit estimation (Eq. (5.1)) using data from S&P and Fitch. The dependent variable ***Split*** *takes the value of one when the difference between the quarterly bank ratings assigned by S&P and Fitch is non-zero, and zero when the ratings assigned by both GRAs are equal. For definitions of the explanatory and control variables, see Sections 5.4.2 and 5.4.4., respectively. The Model (I) includes CCI as a proxy of corruption and the Model (II) includes CI as a proxy of corruption. Full sets of country and year dummies are included in both models. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. All variables are lagged four quarters (t-4). The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table 5.10 Determinants of split bank ratings by Moody's and Fitch

		Dependent variable: *Split*			
Variable	Expected sign	(I)	ME (%)	(II)	ME (%)
Size	+	0.01		0.01	
		(0.17)		(0.14)	
Capital	+/-	0.04		0.04	
		(1.46)		(1.45)	
Profitability	-	-0.34***	-0.22	-0.34***	-0.22
		(-4.28)		(-4.25)	
Liquidity	-	-0.01***	-0.22	-0.01***	-0.22
		(-3.02)		(-3.02)	
Domestcredit	-	0.07***	3.07	0.07***	3.07
		(5.61)		(5.83)	
Ownership	+/-	-0.22		-0.21	
		(-1.02)		(-0.98)	
Sovereign	-	0.25		0.26	
		(1.55)		(1.56)	
Invrating	-	-0.41*	-0.13	-0.40*	-0.13
		(-1.76)		(-1.73)	
CCI	+	-0.20			
		(-0.28)			
CI	+	-		0.15	
				(0.05)	
Observations		560		560	
Country FE		Yes		Yes	
Year FE		Yes		Yes	
Pseudo R-squared		19.5%		19.5%	

The table presents the results of the binary probit estimation (Eq. (5.1)) using data from Moody's and Fitch. The dependent variable ***Split*** *takes the value of one when the difference between the quarterly bank ratings assigned by Moody's and Fitch is non-zero, and zero when the ratings assigned by both GRAs are equal. For definitions of the explanatory and control variables, see Sections 5.4.2 and 5.4.4., respectively. The Model (I) includes CCI as a proxy of corruption and the Model (II) includes CI as a proxy of corruption. Full sets of country and year dummies are included in both models. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. All variables are lagged four quarters (t-4). The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table 5.11 Conservativeness hypothesis - S&P and Moody's

Dependent variable	Independent variable	(I)	ME (%)	(II)	ME (%)
S&PSup	Size	-0.28**	-12.25	-0.28**	-12.31
		(-2.46)		(-2.40)	
	Capital	-0.01		-0.01	
		(-0.24)		(-0.40)	
	Profitability	-0.06		-0.04	
		(-1.06)		(-0.70)	
	Liquidity	-0.00		-0.00	
		(-0.73)		(-0.42)	
	Domestcredit	0.01		0.01	
		(1.48)		(1.33)	
	Ownership	1.80***	0.03	1.79***	0.03
		(5.91)		(5.88)	
	Sovereign	0.79***	21.4	0.76***	20.7
		(6.38)		(6.23)	
	Invrating	0.54*	0.02	0.49	
		(1.67)		(1.46)	
	CCI	-1.35			
		(-1.36)			
	CI			-4.71*	-0.17
				(-1.92)	
	Pseudo R-squared	*38.4%*		*38.3%*	
S&PInf	Size	0.45***	3.90	0.50***	4.31
		(4.72)		(4.92)	
	Capital	0.04*	0.18	0.04**	0.22
		(1.69)		(2.00)	
	Profitability	-0.06		-0.13**	-0.08
		(-1.02)		(-2.35)	
	Liquidity	0.00		0.00	
		(0.33)		(0.50)	
	Domestcredit	0.04***	1.70	0.03***	1.30
		(3.44)		(4.73)	
	Ownership	-0.96***	-0.27	-1.05***	-0.29
		(-4.97)		(-5.39)	
	Sovereign	0.40		0.61***	3.22
		(1.57)		(2.78)	
	Invrating	-1.28***	-0.44	-1.33***	-0.46
		(-5.58)		(-5.40)	
	CCI	1.81**	0.63		
		(2.48)			
	CI			14.26***	4.95
				(4.07)	
	Pseudo R-squared	*29.9%*		*31.9%*	
	Observations	577		577	
	Country FE	YES		YES	
	Year FE	YES		YES	

*The table presents the results of the binary probit estimations (Eqs. (5.2) and (5.3)) using data from S&P and Moody's. The dependent variable S&PSup (S&PInf) takes the value of one when a bank is split rated and S&P assigns a superior (inferior) rating compared to the rating assigned by Moody's, and zero when both GRAs assigned equal ratings or S&P assigns an inferior (superior) rating. For definitions of the explanatory and control variables, see Sections 5.4.2 and 5.4.4., respectively. The Model (I) includes CCI as a proxy of corruption and the Model (II) includes CI as a proxy of corruption. Full sets of country and year dummies are included in both models. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. All variables are lagged four quarters (t-4). The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table 5.12 Conservativeness hypothesis - S&P and Fitch

Dependent variable	Independent variable	(I)	ME (%)	(II)	ME (%)
S&PSup	Size	-0.61***	-26.80	-0.60***	-27.72
		(-3.80)		(-3.68)	
	Capital	0.01		0.00	
		(0.20)		(0.11)	
	Profitability	0.03		-0.03	
		(0.26)		(-0.24)	
	Liquidity	-0.01		-0.01	
		(-1.19)		(-1.20)	
	Domestcredit	-0.01		-0.00	
		(-1.25)		(-0.28)	
	Ownership	0.72***	0.02	0.63**	0.01
		(2.60)		(2.21)	
	Sovereign	-0.51***	-13.62	-0.65***	-17.89
		(-2.73)		(-3.09)	
	Invrating	0.43		0.57	
		(1.06)		(1.40)	
	CCI	0.85*	0.03		
		(1.67)			
	CI			8.65***	0.25
				(3.14)	
	Pseudo R-squared	*35.8%*		*37.9%*	
S&PInf	Size	0.33***	5.04	0.33***	5.01
		(3.60)		(3.53)	
	Capital	0.01		0.01	
		(0.55)		(0.62)	
	Profitability	0.00		0.00	
		(0.01)		(0.01)	
	Liquidity	0.01		0.01	
		(1.49)		(1.57)	
	Domestcredit	-0.02**	-1.94	-0.03**	-2.13
		(-2.16)		(-2.41)	
	Ownership	0.81***	0.29	0.80***	0.29
		(3.64)		(3.74)	
	Sovereign	0.21		0.00	
		(1.21)		(0.01)	
	Invrating	-0.27		-0.28	
		(-1.10)		(-1.14)	
	CCI	0.63			
		(0.88)			
	CI			-5.32*	-2.11
				(-1.83)	
	Pseudo R-squared	*18.6%*		*19.0%*	
Observations		526		526	
Country FE		YES		YES	
Year FE		YES		YES	

*The table presents the results of the binary probit estimations (Eqs. (5.2) and (5.3)) using data from S&P and Fitch. The dependent variable S&PSup (S&PInf) takes the value of one when a bank is split rated and S&P assigns a superior (inferior) rating compared to the rating assigned by Fitch, and zero when both GRAs assigned equal ratings or S&P assigns an inferior (superior) rating. For definitions of the explanatory and control variables, see Sections 5.4.2 and 5.4.4., respectively. The Model (I) includes CCI as a proxy of corruption and the Model (II) includes CI as a proxy of corruption. Full sets of country and year dummies are included in both models. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. All variables are lagged four quarters (t-4). The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table 5.13 Conservativeness hypothesis – Moody’s and Fitch

Dependent variable	Independent variable	(I)	ME (%)	(II)	ME (%)
Moody'sSup	Size	0.00		0.02	
		(0.00)		(0.23)	
	Capital	0.01		0.01	
		(0.21)		(0.26)	
	Profitability	-0.07		-0.09	
		(-1.07)		(-1.31)	
	Liquidity	-0.00		-0.00	
		(-0.89)		(-0.77)	
	Domestcredit	0.07***	6.90	0.07***	6.33
		(6.40)		(6.28)	
	Ownership	-0.98***	-0.38	-1.04***	-0.40
		(-4.68)		(-5.06)	
	Sovereign	0.18		0.25	
		(1.08)		(1.52)	
	Invrating	-0.31		-0.40	
		(-1.16)		(-1.47)	
	CCI	0.55			
		(0.73)			
	CI			5.07**	18.90
				(2.09)	
	Pseudo R-squared	*21.0%*		*21.5%*	
Moody'sInf	Size	-0.03		-0.04	
		(-0.33)		(-0.43)	
	Capital	0.05**	0.73	0.05*	0.73
		(1.96)		(1.94)	
	Profitability	-0.25***	-0.44	-0.25***	-0.44
		(-3.53)		(-3.58)	
	Liquidity	-0.00		-0.01	
		(-0.94)		(-0.98)	
	Domestcredit	-0.02***	-2.33	-0.02***	-2.63
		(-2.95)		(-3.18)	
	Ownership	0.92***	0.20	0.92***	0.20
		(3.26)		(3.27)	
	Sovereign	-0.12		-0.10	
		(-0.49)		(-0.41)	
	Invrating	-0.08		-0.13	
		(-0.46)		(-0.74)	
	CCI	0.23			
		(0.35)			
	CI			-3.35	
				(-1.34)	
	Pseudo R-squared	*25.0%*		*25.2%*	
Observations		560		560	
Country FE		YES		YES	
Year FE		YES		YES	

*The table presents the results of the binary probit estimations (Eqs. (5.2) and (5.3)) using data from Moody's and Fitch. The dependent variable Moody'sSup (Moody'sInf) takes the value of one when a bank is split rated and Moody's assigns a superior (inferior) rating compared to the rating assigned by Fitch, and zero when both GRAs assigned equal ratings or Moody's assigns an inferior (superior) rating. For definitions of the explanatory and control variables, see Sections 5.4.2 and 5.4.4., respectively. The Model (I) includes CCI as a proxy of corruption and the Model (II) includes CI as a proxy of corruption. Full sets of country and year dummies are included in both models. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. All variables are lagged four quarters (t-4). The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table 5.14 Split ratings and rating migration – S&P and Moody's

Panel A.	*UpgS&P*			*DownS&P*		
Variable	(I)	(II)	ME (%)	(I)	(II)	ME (%)
1NSupMoody's	0.34*	0.34	1.34	-0.08	-0.08	
	(1.84)	(1.50)		(-0.55)	(-0.60)	
2NSupMoody's	0.73***	0.73***	5.01	0.02	0.02	
	(3.35)	(2.83)		(0.08)	(0.09)	
1NInfMoody's	-0.07	-0.07		0.05	0.05	
	(-0.29)	(-0.24)		(0.29)	(0.32)	
2NInfMoody's	Merged with 1NInfMoody's			0.02	-0.02	
				(-0.07)	(-0.08)	
S&P Rating	-0.08*	-0.08*	-0.29	0.10***	0.10***	0.58
	(-1.84)	(-1.76)		(3.55)	(4.17)	
Observations	1,720	1,720		1,740	1,740	
Pseudo R^2	16.6%	16.6%		15.0%	15.0%	
Panel B.	*UpgMoody's*			*DownMoody's*		
Variable	(I)	(II)	ME (%)	(I)	(II)	ME (%)
1NSupS&P	0.30	0.30*	1.27	-0.41**	-0.41**	-1.97
	(1.49)	(1.89)		(-2.02)	(-2.13)	
2NSupS&P	0.90***	0.90***	7.15	Merged with 1NSupS&P		
	(2.99)	(3.61)				
1NInfS&P	-0.78***	-0.78***	-2.61	0.10	0.10	
	(-4.48)	(-4.71)		(0.63)	(0.67)	
2NInfS&P	-1.05***	-1.05***	-1.64	0.80***	0.80***	8.75
	(-2.87)	(-2.82)		(4.15)	(4.05)	
Moody's Rating	-0.00	-0.00		0.05*	0.05*	0.33
	(-0.08)	(-0.07)		(1.66)	(1.78)	
Observations	1,705	1,705		1,746	1,746	
Pseudo R^2	21.1%	21.1%		17.8%	17.8%	
Country FE	YES	YES		YES	YES	
Year FE	YES	YES		YES	YES	

The table presents the results of the binary probit estimations (Eqs. (5.4) and (5.5)) using data from S&P and Moody's. In ***Panel A****, the dependent variable* ***UpgS&P (DownS&P)*** *takes the value of one if S&P upgrades (downgrades) the bank 1 or more notches, zero if the rating assigned by S&P has not changed since the previous quarter. In* ***Panel B,*** *the dependent variable* ***UpgMoody's (DownMoody's)*** *takes the value of one if Moody's upgrades (downgrades) the bank 1 or more notches, zero if the rating assigned by Moody's has not changed since the previous quarter. For definitions of the explanatory variables, see Section 5.5.3. The Model I is estimated with Huber–White robust standard errors and Model II presents the estimation clustering at the bank level. Full sets of country and year dummies are included in both models. The z-statistics is reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. All variables are lagged four quarters (t-4). The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table 5.15 Split ratings and rating migration – S&P and Fitch

Panel A.	*UpgS&P*			*DownS&P*		
Variable	(I)	(II)	ME (%)	(I)	(II)	ME (%)
1NSupFitch	1.04***	1.04***	6.14	-0.23*	-0.23*	-1.17
	(5.87)	(5.00)		(-1.70)	(-1.74)	
2NSupFitch	1.19***	1.19***	11.78	-0.07	-0.07	
	(4.45)	(3.95)		(-0.34)	(-0.31)	
1NInfFitch	-0.28	-0.28		0.54***	0.54***	4.50
	(-0.88)	(-1.34)		(2.94)	(2.89)	
2NInfFitch	Merged with 1NInfFitch			0.16	0.16	
				(0.36)	(0.53)	
S&P Rating	-0.15***	-0.15***	-0.54	0.12***	0.12***	0.64
	(-2.85)	(-2.59)		(3.84)	(4.04)	
Observations	1,599	1,599		1,621	1,621	
Pseudo R^2	17.5%	17.5%		16.6%	16.6%	
Panel B.	*UpgFitch*			*DownFitch*		
Variable	(I)	(II)	ME (%)	(I)	(II)	ME (%)
1NSupS&P	0.31	0.31	1.63	-0.80**	-0.80	-1.25
	(1.15)	(1.23)		(-2.41)	(-1.64)	
2NSupS&P	1.40***	1.40***	20.55	Merged with 1NSupS&P		
	(3.54)	(4.38)				
1NInfS&P	-0.06	-0.06		0.49***	0.49***	1.77
	(-0.34)	(-0.29)		(2.83)	(2.58)	
2NInfS&P	-0.26	-0.26		0.47**	0.47*	2.07
	(-0.84)	(-1.20)		(2.08)	(1.95)	
Fitch Rating	-0.08**	-0.08**	-0.33	0.03	0.03	
	(-2.34)	(-2.11)		(0.99)	(0.99)	
Observations	1,629	1,629		1,625	1,625	
Pseudo R^2	13.5%	13.5%		19.2%	19.2%	
Country FE	YES	YES		YES	YES	
Year FE	YES	YES		YES	YES	

*The table presents the results of the binary probit estimations (Eqs. (5.4) and (5.5)) using data from S&P and Fitch. In **Panel A**, the dependent variable **UpgS&P (DownS&P)** takes the value of one if S&P upgrades (downgrades) the bank 1 or more notches, zero if the rating assigned by S&P has not changed since the previous quarter. In **Panel B,** the dependent variable **UpgFitch (DownFitch)** takes the value of one if Fitch upgrades (downgrades) the bank 1 or more notches, zero if the rating assigned by Fitch has not changed since the previous quarter. For definitions of the explanatory variables, see Section 5.5.3. The Model I is estimated with Huber–White robust standard errors and Model II presents the estimation clustering at the bank level. Full sets of country and year dummies are included in both models. The z-statistics is reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. All variables are lagged four quarters (t-4). The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table 5.16 Split ratings and rating migration – Moody's and Fitch

Panel A.	*UpgMoody's*			*DownMoody's*		
Variables	(I)	(II)	ME (%)	(I)	(II)	ME (%)
1NSupFitch	-0.13	-0.13		-0.09	-0.09	
	(-0.74)	(-0.79)		(-0.52)	(-0.54)	
2NSupFitch	0.40**	0.40***	1.96	-0.17	-0.17	
	(2.21)	(2.65)		(-0.89)	(-0.75)	
1NInfFitch	-0.83***	-0.83***	-2.28	0.22*	0.22*	1.61
	(-4.18)	(-4.79)		(1.65)	(1.83)	
2NInfFitch	-0.92**	-0.92***	-1.51	0.71***	0.71***	8.11
	(-2.46)	(-3.29)		(4.22)	(4.01)	
Moody's Rating	-0.01	-0.01		0.11***	0.11***	0.75
	(-0.22)	(-0.16)		(4.86)	(4.23)	
Observations	2,187	2,187		2,241	2,241	
Pseudo R^2	17.5%	17.5%		16.3%	16.3%	
Panel B.	*UpgFitch*			*DownFitch*		
Variables	(I)	(II)	ME (%)	(I)	(II)	ME (%)
1NSupMoodys	0.09	0.09		-0.07	-0.07	
	(0.58)	(0.65)		(-0.36)	(-0.31)	
2NSupMoodys	0.16	0.16		0.05	0.05	
	(0.75)	(0.95)		(0.23)	(0.20)	
1NInfMoody's	0.02	0.02		0.32*	0.32*	1.68
	(0.13)	(0.12)		(1.75)	(1.70)	
2NInfMoody's	-0.71*	-0.71*	-1.89	0.21	0.21	
	(-1.83)	(-1.82)		(1.06)	(1.06)	
Fitch Rating	-0.10***	-0.10***	-0.43	0.12***	0.12***	0.51
	(-3.84)	(-4.33)		(4.78)	(4.75)	
Observations	2,237	2,237		2,241	2,241	
Pseudo R^2	10.5%	10.5%		18.0%	18.0%	
Country FE	YES	YES		YES	YES	
Year FE	YES	YES		YES	YES	

The table presents the results of the binary probit estimations (Eqs. (5.4) and (5.5)) using data from Moody's and Fitch. In ***Panel A****, the dependent variable* ***UpgMoody's (DownMoody's)*** *takes the value of one if Moody's upgrades (downgrades) the bank 1 or more notches, zero if the rating assigned by Moody's has not changed since the previous quarter. In* ***Panel B,*** *the dependent variable* ***UpgFitch (DownFitch)*** *takes the value of one if Fitch upgrades (downgrades) the bank 1 or more notches, zero if the rating assigned by Fitch has not changed since the previous quarter. For definitions of the explanatory variables, see Section 5.5.3. The Model I is estimated with Huber–White robust standard errors and Model II presents the estimation clustering at the bank level. Full sets of country and year dummies are included in both models. The z-statistics is reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. All variables are lagged four quarters (t-4). The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Chapter 5 Figures

Figure 5.1 Distribution of emerging bank quarterly ratings by rating score, all GRAs

Figure A. S&P and Moody's

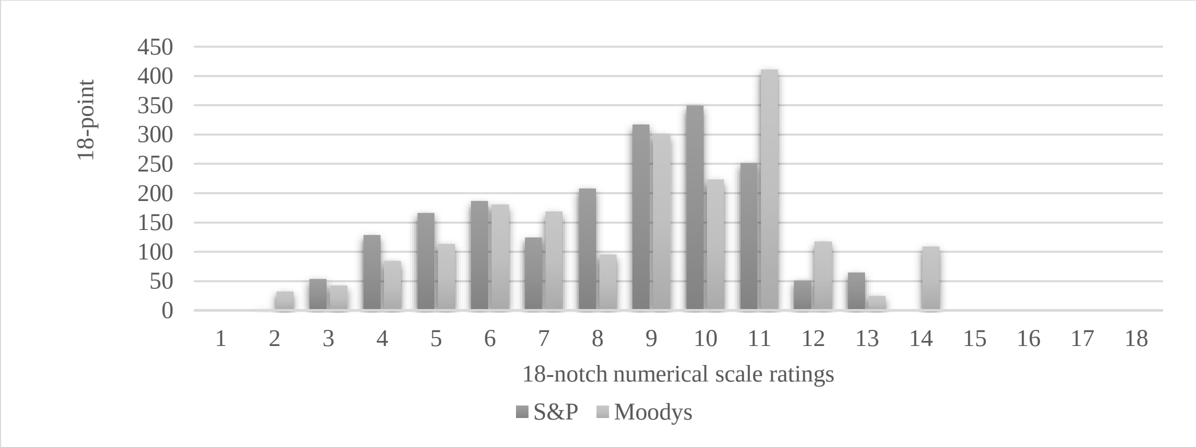


Figure B. S&P and Fitch

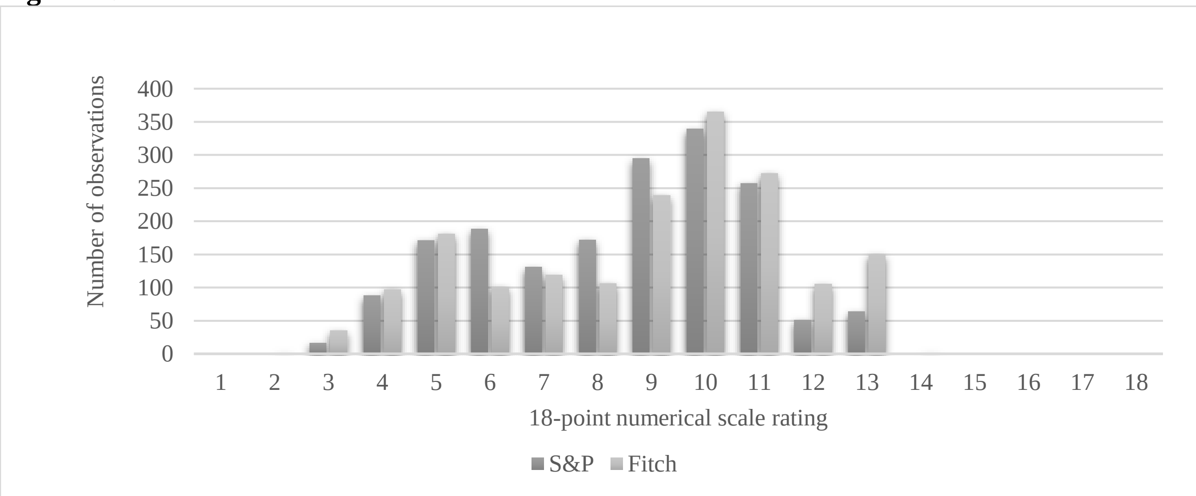
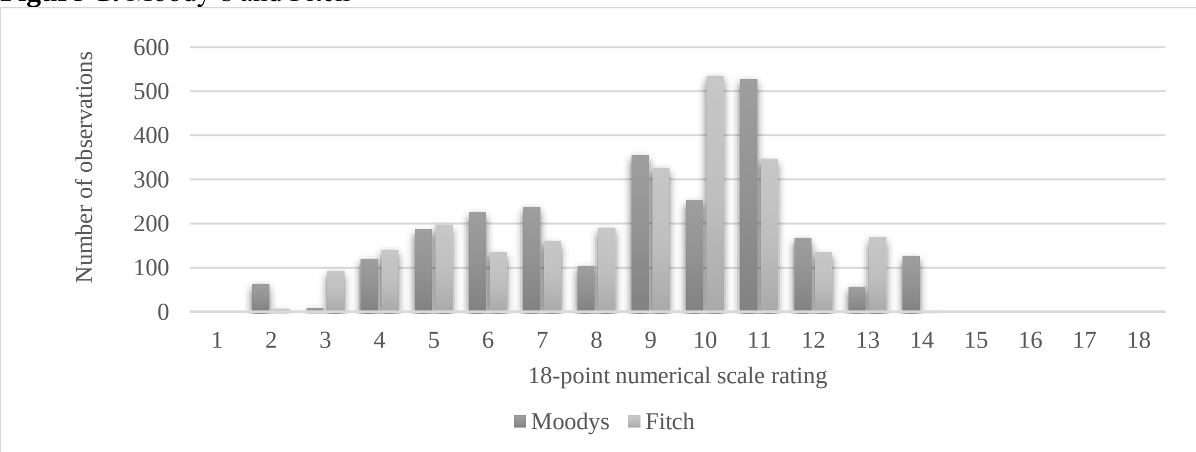


Figure C. Moody's and Fitch



The figures A, B and C present the distribution of the bank quarterly ratings of the sampled banks for each pair of GRAs (S&P and Moody's, S&P and Fitch and Moody's and Fitch, respectively) during the period October 2008 to December 2015. The credit rating scale of each GRA is transformed into an 18-point numerical scale. The Figures are based on the data from the full sample, not matched with financial data.

Figure 5.2 Distribution of split bank ratings, only considering the lower rating assigned

Figure A. S&P and Moody's

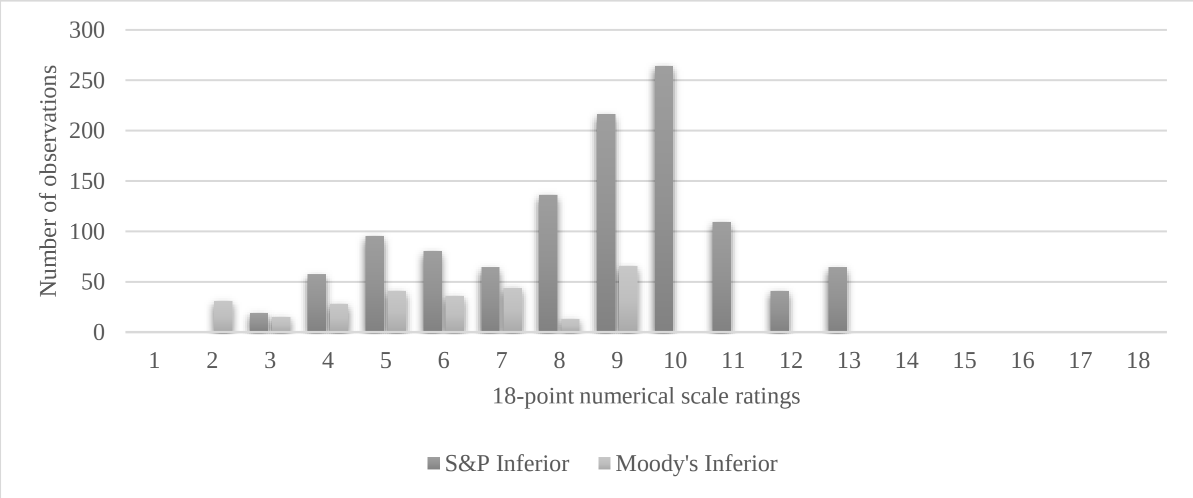


Figure B. S&P and Fitch

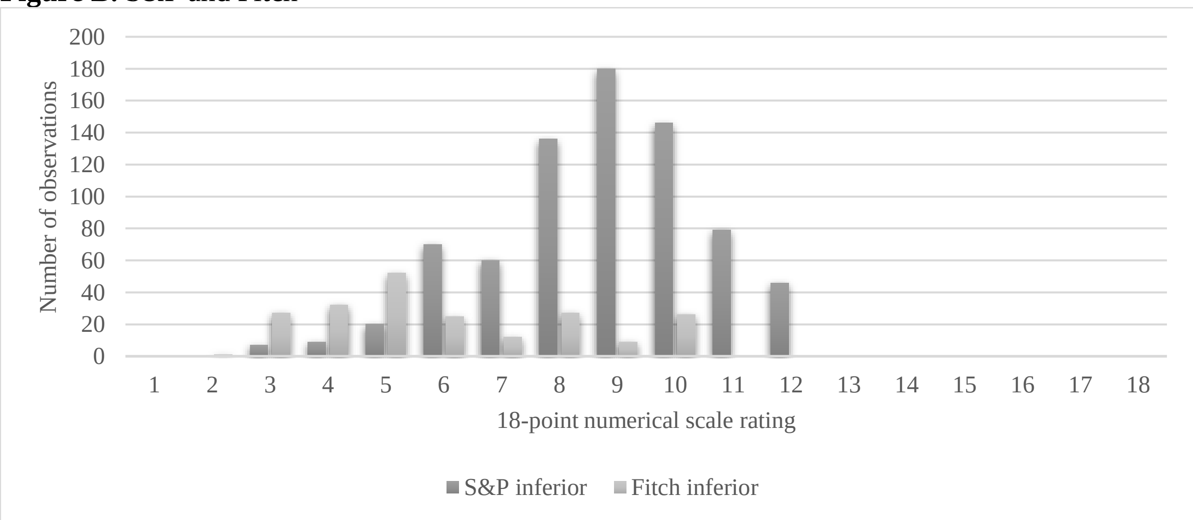
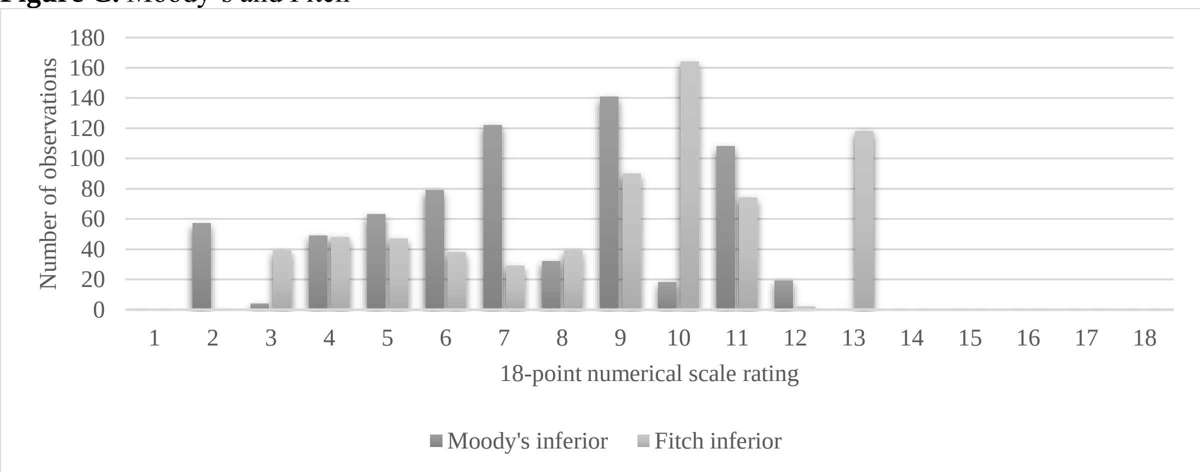
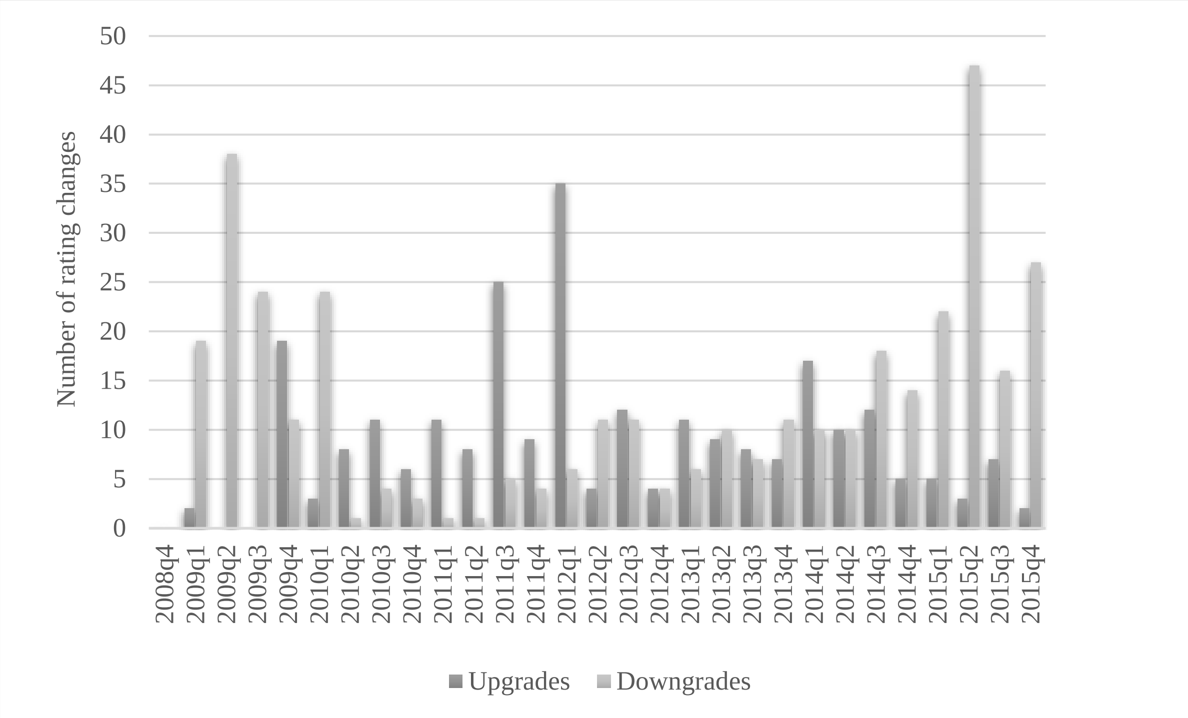


Figure C. Moody's and Fitch



The figures A, B and C present the distribution of lower bank ratings. Namely, the number of observations where one of the GRAs assigns lower bank ratings compared to the other GRA, when split bank ratings occur, for each pair of GRAs (S&P and Moody's, S&P and Fitch and Moody's and Fitch, respectively). The bank ratings reported are based on the 18-point numerical scale, for each pair of GRAs. The credit rating scale of each GRA is transformed into an 18-point numerical scale. The Figures are based on the data from the full sample, not matched with financial data.

Figure 5.3 Bank rating changes by S&P, Moody's and Fitch



The figure presents the evolution of bank rating downgrades and upgrades by S&P, Moody's and Fitch using the full sample, not matched with the financial data for the period October 2008 to December 2015.

Appendix

Table A 5.1 Determinants of split bank ratings by S&P and Moody's – Ordered probit model

		Dependent variable: *OrdSplit*							
			ME (%)				ME (%)		
Variable	Expected sign	(I)	1	2	3	(II)	1	2	3
Size	+	0.15*	0.01	0.03	0.00	0.16**	0.01	0.03	0.00
		(1.91)				(2.06)			
Capital	+/-	0.01				0.02			
		(0.84)				(1.11)			
Profitability	-	-0.02				-0.06			
		(-0.52)				(-1.22)			
Liquidity	-	-0.00				-0.00			
		(-1.37)				(-1.34)			
Domestcredit	+	0.01				0.00			
		(0.80)				(0.23)			
Ownership	+/-	-0.22				-0.24			
		(-1.46)				(-1.57)			
Sovereign	-	0.03				0.15			
		(0.21)				(1.12)			
Invrating	-	-0.47**	-2.74	-9.36	-1.17	-0.46**	-2.73	-9.06	-1.07
		(-2.36)				(-2.26)			
CCI	+	0.41							
		(0.80)							
CI	+					7.40***	0.67	1.39	0.14
						(3.07)			
Observations		577				577			
Country FE		Yes				Yes			
Year FE		Yes				Yes			
Pseudo R-squared		7.7%				8.6%			

The table presents the results of the ordered probit specification (Eq. (5.6)) using data from S&P and Moody's. The dependent variable ***OrdSplit*** *corresponds to the absolute value of the quarterly rating differences of S&P and Moody's (see further details in Section 5.6.4.1). For definitions of the explanatory and control variables, see Sections 5.4.2 and 5.4.4., respectively. The Model (I) includes CCI as a proxy of corruption and the Model (II) includes CI as a proxy of corruption. Full sets of country and year dummies are included in both models. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. All variables are lagged four quarters (t-4). The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table A 5.2 Determinants of split bank ratings by S&P and Fitch– Ordered probit model

		Dependent variable: *OrdSplit*							
			ME (%)				ME (%)		
Variable	Expected sign	(I)	1	2	3	(II)	1	2	3
Size	+/-	0.23***	0.06	0.03	0.00	0.23***	0.06	0.03	0.00
		(2.67)				(2.69)			
Capital	+/-	0.04**	1.03	0.58	0.06	0.04**	1.07	0.60	0.06
		(2.12)				(2.20)			
Profitability	-	-0.12*	-2.89	-1.62	-0.17	-0.13*	-3.15	-1.77	-0.18
		(-1.73)				(-1.91)			
Liquidity	-	0.00				0.00			
		(0.29)				(0.31)			
Domestcredit	+	-0.03***	-0.01	-0.00	-0.00	-0.04***	-0.01	-0.00	-0.00
		(-3.98)				(-4.17)			
Ownership	+/-	0.99***	27.73	9.04	0.76	0.96***	26.91	8.89	0.74
		(5.09)				(5.02)			
Sovereign	-	-0.18				-0.19			
		(-1.25)				(-1.30)			
Invrating	-	0.02				0.03			
		(0.10)				(0.14)			
CCI	+	0.39							
		(0.63)							
CI	+					1.00			
						(0.43)			
Observations		526				526			
Country FE		YES				YES			
Year FE		YES				YES			
Pseudo R-squared		14.1%				14.1%			

The table presents the results of the ordered probit specification (Eq. (5.6)) using data from S&P and Fitch. The dependent variable ***OrdSplit*** *corresponds to the absolute value of the quarterly rating differences of S&P and Fitch (see further details in Section 5.6.4.1). For definitions of the explanatory and control variables, see Sections 5.4.2 and 5.4.4., respectively. The Model (I) includes CCI as a proxy of corruption and the Model (II) includes CI as a proxy of corruption. Full sets of country and year dummies are included in both models. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. All variables are lagged four quarters (t-4). The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table A 5.3 Determinants of split bank ratings by Moody's and Fitch– Ordered probit model

		Dependent variable: *OrdSplit*							
			ME (%)				ME (%)		
Variable	Expected sign	(I)	1	2	3	(II)	1	2	3
Size	+/-	-0.03				-0.04			
		(-0.40)				(-0.53)			
Capital	+/-	0.02				0.02			
		(0.95)				(0.89)			
Profitability	-	-0.20***	-3.97	-2.86	-0.35	-0.19***	-3.79	-2.73	-0.32
		(-3.59)				(-3.47)			
Liquidity	-	-0.01***	-0.21	-0.15	-0.02	-0.01***	-0.21	-0.15	-0.02
		(-2.74)				(-2.78)			
Domestcredit	+	0.07***	1.33	0.96	0.12	0.07***	1.35	0.98	0.11
		(7.97)				(8.21)			
Ownership	+/-	0.05				0.08			
		(0.28)				(0.50)			
Sovereign	-	-0.05				-0.07			
		(-0.35)				(-0.52)			
Invrating	-	-0.15				-0.13			
		(-0.74)				(-0.61)			
CCI	+	-0.42							
		(-0.73)							
CI	+					-2.51			
						(-1.16)			
Observations		560				560			
Country FE		Yes				Yes			
Year FE		Yes				Yes			
Pseudo R-squared		15.9%				16.0%			

The table presents the results of the ordered probit specification (Eq. (5.6)) using data from Moody's and Fitch. The dependent variable ***OrdSplit*** *corresponds to the absolute value of the quarterly rating differences of Moody's and Fitch (see further details in Section 5.6.4.1). For definitions of the explanatory and control variables, see Sections 5.4.2 and 5.4.4., respectively. The Model (I) includes CCI as a proxy of corruption and the Model (II) includes CI as a proxy of corruption. Full sets of country and year dummies are included in both models. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. All variables are lagged four quarters (t-4). The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table A 5.4 Ordered probit model for split ratings and rating migration – S&P and Moody's

Panel A.	*OrdUpgS&P*				*OrdDownS&P*			
			ME (%)				ME (%)	
Variable	(I)	(II)	1	2	(I)	(II)	1	2
1NSupMoody's	0.37**	0.37*	1.42	0.11	-0.09	-0.09		
	(2.01)	(1.65)			(-0.63)	(-0.70)		
2NSupMoody's	0.71***	0.71***	4.50	0.48	-0.02	-0.02		
	(3.37)	(2.86)			(-0.09)	(-0.10)		
1NInfMoody's	-0.07	-0.07			0.03	0.03		
	(-0.28)	(-0.23)			(0.19)	(0.20)		
2NInfMoody's	Merged with 1NInfMoody's				0.01	0.01		
					(0.04)	(0.05)		
S&P Rating	-0.09**	-0.09*	-0.32	-0.02	0.09***	0.09***	0.47	0.03
	(-2.09)	(-1.96)			(3.12)	(3.57)		
Observations	1,720	1,720			1,740	1,740		
Country FE	YES	YES			YES	YES		
Year FE	YES	YES			YES	YES		
Pseudo R^2	15.0%	15.0%			13.7%	13.7%		

Panel B.	*OrdUpgMoody's*					*OrdDownMoody's*				
			ME (%)					ME (%)		
Variable	(I)	(II)	1	2	3	(I)	(II)	1	2	3
1NSupS&P	0.33*	0.33*	1.48	0.26	0.01	-0.36*	-0.36*	-1.55	-0.29	-0.02
	(1.66)	(1.71)				(-1.79)	(-1.80)			
2NSupS&P	0.64**	0.64**	4.00	0.85	0.06	Merged with 1NSupS&P				
	(2.36)	(2.02)								
1NInfS&P	-0.76***	-0.76***	-2.73	-0.45	-0.03	0.12	0.12			
	(-4.62)	(-4.82)				(0.80)	(0.84)			
2NInfS&P	-1.08***	-1.08***	-1.93	-0.26	-0.01	0.81***	0.81***	6.99	2.02	0.23
	(-3.11)	(-3.07)				(4.42)	(4.20)			
Moody's Rating	0.03	0.03	0.11	0.02	0.00	0.05	0.05*	0.26	0.05	-0.00
	(1.08)	(0.67)				(1.55)	(1.67)			
Observations	1,705	1,705				1,746	1,746			
Country FE	YES	YES				YES	YES			
Year FE	YES	YES				YES	YES			
Pseudo R^2	14.5%	14.5%				14.7%	14.7%			

The table presents the results of the ordered probit estimations (Eqs. (5.4) and (5.5)) using data from S&P and Moody's. In ***Panel A****, the dependent variable* ***OrdUpgS&P (OrdDwnS&P)*** *takes the value of 1 or 2 if S&P bank rating is upgraded (downgraded) by 1 or 2 or more notches, respectively. In* ***Panel B****, the dependent variable* ***OrdUpgMoody's (OrdDwnMoody's)*** *takes the value of 1, 2 or 3 if Moody's bank rating is upgraded (downgraded) by 1, 2 or 3 or more notches, respectively. For definitions of the explanatory variables see Section 5.5.3. The Model (I) is estimated with Huber–White robust standard errors and Model (II) presents the estimation clustering at the bank level. Also, z-statistics are reported beneath each coefficient. Full sets of country and year dummies are included in both models. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table A 5.5 Ordered probit model for split ratings and rating migration – S&P and Fitch

Panel A.	*OrdUpgS&P*				*OrdDownS&P*			
			ME (%)				ME (%)	
Variable	(I)	(II)	1	2	(I)	(II)	1	2
1NSupFitch	1.00***	1.00***	5.44	0.40	-0.25*	-0.25*	-1.23	-0.04
	(5.31)	(4.76)			(-1.86)	(-1.89)		
2NSupFitch	1.12***	1.12***	9.69	1.01	-0.07	-0.07		
	(4.13)	(3.80)			(-0.33)	(-0.30)		
1NInfFitch	-0.32	-0.32			0.53***	0.53***	4.27	0.22
	(-1.01)	(-1.44)			(2.81)	(2.69)		
2NInfFitch	Merged with 1NInfFitch				0.15	0.15		
					(0.33)	(0.46)		
S&P Rating	-0.16***	-0.16***	-0.55	-0.03	0.11***	0.11***	0.58	0.02
	(-3.07)	(-2.77)			(3.51)	(3.61)		
Observations	1,599	1,599			1,621	1,621		
Country FE	YES	YES			YES	YES		
Year FE	YES	YES			YES	YES		
Pseudo R^2	16.4%	16.4%			15.3%	15.3%		

Panel B.	*OrdUpgFitch*					*OrdDownFitch*				
			ME (%)					ME (%)		
Variable	(I)	(II)	1	2	3	(I)	(II)	1	2	3
1NSupS&P	0.37	0.37				-0.84**	-0.84*	-1.30	-0.01	-0.01
	(1.33)	(1.41)				(-2.57)	(-1.70)			
2NSupS&P	1.50***	1.50***	19.42	3.12	1.15			Merged with 1NSupS&P		
	(3.67)	(4.07)								
1NInfS&P	-0.08	-0.08				0.45***	0.45**	1.60	0.03	0.02
	(-0.41)	(-0.36)				(2.69)	(2.46)			
2NInfS&P	-0.30	-0.30				0.45**	0.45*	1.95	0.03	0.03
	(-0.98)	(-1.38)				(2.09)	(1.94)			
Fitch Rating	-0.07**	-0.07*	-0.28	-0.02	-0.00	0.03	0.03			
	(-2.18)	(-1.91)				(0.79)	(0.79)			
Observations	1,629	1,629				1,625	1,625			
Country FE	YES	YES				YES	YES			
Year FE	YES	YES				YES	YES			
Pseudo R^2	12.9%	12.9%				18.0%	18.0%			

*The table presents the results of the ordered probit estimations (Eqs. (5.4) and (5.5)) using data from S&P and Fitch. In **Panel A**, the dependent variable **OrdUpgS&P (OrdDwnS&P)** takes the value of 1 or 2 if S&P bank rating is upgraded (downgraded) by 1 or 2 or more notches, respectively. In **Panel B**, the dependent variable **OrdUpgFitch (OrdDwnFitch)** takes the value of 1, 2 or 3 if Fitch bank rating is upgraded (downgraded) by 1, 2 or 3 or more notches, respectively. For definitions of the explanatory variables see Section 5.5.3. The Model (I) is estimated with Huber–White robust standard errors and Model (II) presents the estimation clustering at the bank level. Also, z-statistics are reported beneath each coefficient. Full sets of country and year dummies are included in both models. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table A 5.6 Ordered probit model for split ratings and rating migration – Moody's and Fitch

Panel A.	*OrdUpgMoody's*					*OrdDownMoody's*				
			ME (%)					ME (%)		
Variable	(I)	(II)	1	2	3	(I)	(II)	1	2	3
1NSupFitch	-0.12	-0.12				-0.11	-0.11			
	(-0.71)	(-0.79)				(-0.69)	(-0.70)			
2NSupFitch	0.46**	0.46***	1.92	0.38	0.02	-0.21	-0.21			
	(2.48)	(2.95)				(-1.11)	(-0.91)			
1NInfFitch	-0.81***	-0.81***	-1.91	-0.31	-0.01	0.19	0.19			
	(-4.07)	(-4.65)				(1.42)	(1.54)			
2NInfFitch	-0.90**	-0.90***	-1.30	-0.18	-0.01	0.65***	0.65***	5.77	1.19	0.30
	(-2.40)	(-3.47)				(3.95)	(3.64)			
Moody's Rating	-0.01	-0.01				0.11***	0.11***	0.65	0.10	0.02
	(-0.28)	(-0.20)				(4.95)	(4.40)			
Observations	2,187	2,187				2,241	2,241			
Country FE	YES	YES				YES	YES			
Year FE	YES	YES				YES	YES			
Pseudo R^2	15.7%	15.7%				14.0%	14.0%			
Panel B.	*OrdUpgFitch*					*OrdDownFitch*				
			ME (%)					ME (%)		
Variable	(I)	(II)	1	2		(I)	(II)	1	2	3
1NSupMoody's	0.10	0.10				-0.06	-0.06			
	(0.67)	(0.74)				(-0.33)	(-0.29)			
2NSupMoody's	0.19	0.19				0.03	0.03			
	(0.87)	(1.09)				(0.15)	(0.13)			
1NInfMoody's	0.04	0.04				0.32*	0.32*	1.62	0.04	0.02
	(0.22)	(0.20)				(1.78)	(1.71)			
2NInfMoody's	-0.69*	-0.69*	-1.78	-0.10		0.24	0.24			
	(-1.78)	(-1.77)				(1.24)	(1.24)			
Fitch Rating	-0.10***	-0.10***	-0.41	-0.03		0.12***	0.12***	0.46	0.01	0.00
	(-3.75)	(-4.43)				(4.53)	(4.47)			
Observations	2,237	2,237				2,241	2,241			
Country FE	YES	YES				YES	YES			
Year FE	YES	YES				YES	YES			
Pseudo R^2	9.7%	9.7%				16.3%	16.3%			

*The table presents the results of the ordered probit estimations (Eqs. (5.4) and (5.5)) using data from Moody's and Fitch. In **Panel A**, the dependent variable **OrdUpgMoody's (OrdDwnMoody's)** takes the value of 1,2 or 3 if Moody's bank rating is upgraded (downgraded) by 1, 2 or 3 or more notches, respectively. In **Panel B**, the dependent variable **OrdUpgFitch (OrdDwnFitch)** takes the value of 1 or 2 (1,2 or 3)if Fitch bank rating is upgraded (downgraded) by 1 or 2 or more notches (1, 2 or 3 or more notches), respectively. For definitions of the explanatory variables see Section 5.5.3. The Model (I) is estimated with Huber–White robust standard errors and Model (II) presents the estimation clustering at the bank level. Also, z-statistics are reported beneath each coefficient. Full sets of country and year dummies are included in both models. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table A 5.7 Determinants of split bank ratings across all three GRAs

		Dependent variable: *SplitGRAs*			
Variable	Expected sign	(I)	ME (%)	(II)	ME (%)
Size	+	0.15		0.15	
		(1.30)		(1.29)	
Capital	+/-	0.05**	1.20	0.05**	1.21
		(2.01)		(2.03)	
Profitability	-	-0.10		-0.10	
		(-1.39)		(-1.41)	
Liquidity	-	-0.01*	-0.21	-0.01*	-0.22
		(-1.80)		(-1.86)	
Domestcredit	-	-0.01*	-0.28	-0.02***	-0.43
		(-1.72)		(-2.73)	
Ownership	+/-	0.29		0.31	
		(1.21)		(1.30)	
Sovereign	-	-0.41**	-10.72	-0.46**	-11.72
		(-2.10)		(-2.32)	
Invrating	-	-0.03		-0.03	
		(-0.37)		(-0.40)	
CCI	+	0.01			
		(0.01)			
CI	+			-3.29	
				(-1.27)	
Observations		471		471	
Country FE		Yes		Yes	
Year FE		Yes		Yes	
Pseudo R-squared		25.2%		25.5%	

*The table presents the results of the binary probit specification (Eq. (5.1)) using the data of S&P, Moody's and Fitch. The dependent variable **SplitGRAs** is a dummy variable that takes the value of one when the bank has split ratings by any pair of GRAs, zero otherwise. The Model (I) includes the variable CCI and Model (II) includes the variable CI. Full sets of country and year dummies are included in both models. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. All variables are lagged four quarters (t-4). The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table A 5.8 Split bank ratings across the three GRAs and rating migrations

Panel A.	*S&P*			
Variable	UpgS&P	ME%	DownS&P	ME%
SupS&P	0.83**	5.21	0.56**	4.85
	(2.22)		(2.04)	
InfS&P	0.58		-0.47	
	(1.47)		(-1.60)	
SupMoody's	0.19		0.29	
	(0.57)		(0.90)	
InfMoody's	-0.77*	-1.23	-0.34	
	(-1.94)		(-1.36)	
SupFitch	0.29		0.18	
	(1.41)		(0.92)	
InfFitch	-0.97***	-2.35	0.24	
	(-3.86)		(1.20)	
S&P Rating	-0.11		0.10**	0.52
	(-1.50)		(2.54)	
Observations	*1,262*		*1,278*	
Pseudo R^2	*21.6%*		*15.4%*	
Panel B.	*Moody's*			
Variable	UpgMoody's	ME%	DownMoody's	ME%
SupS&P	0.04		-0.31	
	(0.12)		(-0.75)	
InfS&P	-0.86**	-3.52	0.19	
	(-2.45)		(0.54)	
SupMoody's	0.02		0.48	
	(0.07)		(1.36)	
InfMoody's	-0.03		0.10	
	(-0.10)		(0.34)	
SupFitch	0.29		-0.84***	-3.52
	(1.39)		(-4.10)	
InfFitch	-0.25		-0.41**	-1.66
	(-0.88)		(-2.18)	
Moody's Rating	-0.07		0.05	
	(-1.39)		(1.24)	
Observations	1,260		1,275	
Pseudo R^2	22.3%		19.9%	

(Continued on next page)

Table A 5.8 (Continued)

Panel C.	*Fitch*			
Variable	*UpgFitch*	ME%	*DownFitch*	ME%
SupS&P	0.88**	6.89	1.07**	6.66
	(2.25)		(2.44)	
InfS&P	-0.04		-0.22	
	(-0.12)		(-0.71)	
SupMoody's	-0.23		0.79**	1.59
	(-0.77)		(2.57)	
InfMoody's	-1.03***	-1.82	-0.48	
	(-3.23)		(-1.23)	
SupFitch	-0.09		0.58***	1.44
	(-0.40)		(2.62)	
InfFitch	0.25		-0.70***	-1.26
	(0.97)		(-2.62)	
Fitch Rating	-0.07*	-0.26	0.06	
	(-1.80)		(1.46)	
Observations	1,282		1,277	
Pseudo R^2	12.7%		23.8%	
Country FE	Yes		Yes	
Year FE	Yes		Yes	

The table presents the results of the binary probit estimations (Eqs. (5.7) and (5.8)). The dependent variable $\boldsymbol{UpgGRA^{A}_{i,j,t}}$*(*$\boldsymbol{DownGRA^{A}_{i,j,t}}$*) takes the value of one if GRA A (**Panel A:** S&P**, Panel B:** Moody's, **Panel C:** Fitch) upgrades (downgrades) the bank one or more notches, zero if the rating assigned by GRA A does not change. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Chapter 6 The systematic component of split bank ratings in emerging economies

6.1 Introduction

Since the financial crisis of 2007-2009, the interest of academia in the mechanisms of transmission of sovereign risk to bank risk has risen. Regulators have identified four channels of transmission of sovereign risk to the banking industry: bank portfolio holdings of public debt, when sovereign debt is used as collateral by banks (collateral channel), contagion from sovereign ratings to bank ratings (rating channel) and a guarantee channel that corresponds to the banks' implicit government guarantee (BIS, 2011). Previous research on the rating channel shows that sovereign rating changes have a strong effect on bank rating changes (Williams et al., 2013; Huang and Shen, 2015), bank fundamentals (Adelino and Ferreira, 2016) and bank valuations (Williams et al., 2015). Research suggests that the transmission of sovereign risk to the banking sector through sovereign ratings is stronger in emerging economies, which is partly explained by the low government transparency, weak governmental controls on the financial system and the effect of the sovereign ceiling (Williams et al., 2013).

Despite the substantial evidence on the link between bank risk and sovereign risk through the rating channel, the credit rating literature remains silent on the role of sovereign risk in bank rating disagreements (e.g. Morgan, 2002; Iannotta, 2006). Chapter 5 shows that the proxies of the macroeconomic and institutional environment have a significant impact on split bank ratings. However, Chapter 5 focuses on the evaluation of bank-specific factors (idiosyncratic factors) as drivers of bank split ratings. Thus, the impact of systematic factors, such as the sovereign risk, in GRAs' rating disagreements is not examined. Chapter 6 addresses this void in split rating literature. Since sovereign opacity has a significant impact on the bank's risk-taking behaviour in emerging economies (Chen et al., 2015), Chapter 6 examines the impact of split sovereign ratings, as proxies of sovereign opacity, on split bank ratings. Prior literature suggests that split sovereign ratings reflect the government's opacity because they are signals of the ambiguity of the sovereigns' creditworthiness (Vu et al., 2015) and a measure of the political risk and information quality in emerging economies (Vu et al., 2017). Therefore, the first question investigates the rating channel for transmission of sovereign risk to bank risk, using split sovereign ratings as a proxy of the systematic factors that may explain the disagreements of CRAs on bank ratings.

There is strong evidence of the lopsided behaviour when split ratings occur in banks, corporates and sovereigns. Namely, one GRA tends to assign ratings in a more conservative manner (assign lower ratings) than the other GRA when split ratings occur (see section 3.2.4). The literature on bank and corporate split ratings find that Moody's is the most conservative GRA when examining its rating changes against S&P (Morgan, 2002; Livingston et al., 2010), while studies of split sovereign ratings find that S&P is the most conservative GRA (Vu et al., 2017). Chapter 5 shows that S&P tends to behave conservative when split bank ratings occur with Fitch or with Moody's in emerging economies. The lopsided rating behaviour observed in banks and sovereigns motivates the second research question of this Chapter, which investigates whether split bank ratings have an asymmetric response to superior or inferior sovereign ratings. When a GRA tends to assign lower sovereign ratings, this may reflect the GRAs' stronger perception of uncertainty on the political and institutional environment of the country, compared to the other GRA. As one of the channels of transmission of the sovereign risk to the banking sector are ratings, it is highly likely that the GRAs' tendency to assign an inferior sovereign rating is mirrored in the GRAs' bank rating assignments when split ratings occur.

The third research question of this Chapter analyses whether split bank ratings sensitivity to split sovereign ratings in emerging economies is stronger when the ceiling effect[119] takes place. Williams et al. (2013) show, for emerging economies, that GRAs' bank rating actions in the same direction as of sovereign rating actions, are more likely to occur when bank ratings are equal or superior to sovereign ratings. Likewise, Huang and Shen (2015) find that sovereign rating changes have more influence on bank rating changes when the ceiling effect occurs. Furthermore, they show that S&P has a high proportion of bank rating changes taken at the same time as sovereign rating changes when the ceiling effect occurs. Thus, the literature findings suggest that bank ratings have a strong sensitivity to sovereign ratings when the sovereign ceiling occurs.

In summary, Chapter 4 considers two main issues, the sensitivity of split bank ratings to split sovereign ratings and the effect of the sovereign ceiling on split bank ratings. To examine the three research questions of the Chapter, a sample of quarterly bank and sovereign ratings assigned by S&P, Fitch and Moody's in emerging economies from October 2008 to December 2015, is employed. Specifically, the sample comprises: 1,898 observations (92 banks) from 9 countries rated jointly by S&P and Moody's; 1,767 observations (95 banks) from 10 countries rated jointly by S&P and Fitch; and 2,423 observations (111 banks) from 10 countries rated jointly by Moody's and Fitch during October 2008 to December 2015.

[119] In this Chapter, the ceiling effect is a dummy variable that takes the value of one when bank ratings are equal or higher than the sovereign rating.

For the first and third research question, the results show that split sovereign ratings and the ceiling effect significantly impact split bank ratings, implying that both are accurate measures of the systematic component of split ratings. Moreover, the results suggest that the transmission of sovereign risk through the rating channel, investigated for sovereign and bank rating actions by Williams et al. (2013) and Huang and Shen (2015), is also observed in split bank and split sovereign ratings. When S&P assigns superior (inferior) sovereign ratings, the probability of S&P assigning superior (inferior) bank ratings than Moody's or Fitch increases. Likewise, the likelihood of Moody's assigning superior (inferior) bank ratings than Fitch, increases when Moody's assigns superior (inferior) sovereign ratings.

Regarding the second research question, the descriptive statistics show that S&P tends to assign bank and sovereign ratings in a more conservative manner than Moody's or than Fitch. Furthermore, the estimations show that when S&P assigns inferior sovereign ratings than Moody's or Fitch, it has a significant effect on the probabilities of S&P assigning inferior bank ratings. For banks and sovereigns jointly rated by Fitch and Moody's, the descriptive analysis shows that Fitch tends to assign lower ratings. Moreover, the probability of Moody's assigning inferior bank ratings decreases significantly when Moody's assigns superior sovereign ratings (i.e. when Fitch assigns lower sovereign ratings). The estimations also show that the effect of sovereign opacity has more economic significance for split bank ratings between S&P and Fitch than between S&P and Moody's.

Regarding the third research question, the results suggest that inferior bank rating assignments by a given GRA are more sensitive to split sovereign ratings, when the ceiling effect from the competitor GRA takes place. Higher sensitivity to the ceiling effect is observed in split bank ratings of two-or-more-notches than on split bank ratings of one-notch. Thus, if S&P assigns inferior sovereign ratings than Moody's (Fitch), the probability of S&P assigning two-or-more-notches inferior bank ratings is higher than for one-notch split bank ratings, when Moody's (Fitch) ceiling effect occurs. Likewise, for banks jointly rated by Moody's and Fitch, inferior sovereign rating assignments by Moody's have stronger effects on the probability of Moody's assigning two-or-more-notches inferior bank ratings, when Fitch ceiling occurs. The results suggest that when a given GRA perceives more opacity on the sovereign (i.e. assigns inferior sovereign ratings), and the other GRA perceives that the bank has strong financial performance, even without considering the government support, and assigns a bank rating equal or higher than the sovereign rating, the probability of larger rating differential between these GRAs increases. Contrary to the results observed in inferior bank ratings, the sensitivity of S&P

superior bank rating assignments than Moody's (Fitch), when S&P assigns inferior (superior) sovereign ratings than Moody's (Fitch), is higher when S&P ceiling effect occurs, whether the bank split is of one-notch or of two-or-more-notches. The latter results imply that S&P is less influenced by the other two GRAs when assigning superior bank ratings. In contrast, for banks and sovereigns jointly rated by Moody's and Fitch, the sensitivity of Moody's assigning superior bank ratings when Moody's assigns inferior sovereign ratings, is higher if Fitch ceiling effect prevails, whether the bank splits are of one-notch or of two-or-more-notches. In sum, the results confirm that S&P rating assignments, which is the GRA that tends to assign bank and sovereign ratings in a more conservative manner compared to Moody's or Fitch, have a significant influence on the rating assignments of the other GRAs. Similarly, a tendency to assign lower bank and sovereign ratings by Fitch has a strong effect on Moody's bank rating assignments.

The remainder of the Chapter is organised as follows. Section 6.2 presents the literature review. Section 6.3 details the research questions and hypotheses, Section 6.4 describes the data used in the estimations, Section 6.5 presents the methodology, Section 6.6 discusses the evidence from the empirical model and the robustness tests and Section 6.8 concludes the Chapter.

6.2 Literature review

6.2.1 Systemic, systematic and idiosyncratic risk of the banks

The financial crisis of 2007-2009 brings awareness of the high interconnectedness within the banking industry and with the real economy and the risk it poses under financial distress (Correa and Sapriza, 2014). The effects of the financial turmoil encourage research on the mechanisms to predict systemic risk. Acharya et al. (2017) construct a measure of systemic risk using the financial crisis of 2007-2009 as a framework. To test the model, they apply the Marginal Expected Shortfall (MES)[120] to the banking industry and find that MES can accurately predict which type of financial institutions will contribute to the systemic risk during a crisis. Moreover, they show that banks with brokerage activities and security dealers are systemically riskier than insurance firms and banks focused on deposits.

The determinants of systemic risk also gained academic attention after the crisis. Drehmann and Tarashev (2011) compare a proxy of systemic risk: expected shortfall (ES) at the 99% level,[121] against bank characteristics: size, interbank lending and interbank borrowing on 20 internationally relevant banks between 2006 and 2009. They find that bank size is a strong predictor of banks' systemic relevance compared to interbank lending and interbank borrowing, concluding that bank size is a good proxy of ES. Fiordelisi and Marqués-Ibañez (2013) analyse European banks during 1997 to 2007 and find that default risk[122] strongly influences systemic and systematic risk,[123] concluding that banks which could increase systemic risk in case of default, should have tighter market regulation. Laeven et al. (2016) use a sample of commercial banks and bank holdings in 56 developing and developed countries from 2000 to 2012, and also find evidence of a strong influence of bank size on systemic risk, measured by CoVar and SRisk.[124] They also note that having a strong capital is essential for

[120] According to Acharya et al. (2017), each bank default loss has an expected contribution to a financial crisis called Systemic Expected shortfall (SES). The Marginal Expected Shortfall (MES) are the losses in the tail of the system's loss distribution, measuring how expose is a bank to aggregate tail shocks..
[121] Drehmann and Tarashev (2011) define expected shortfall as the "expected aggregate loss to non-bank creditors, conditional on such a loss exceeding the 99th percentile of the underlying probability distribution".
[122] Fiordelisi and Marqués-Ibañez (2013) use three different measures of default risk: z-score, Bond ratings by Moody's, and Moody's Expected Default Frequency.
[123] Weiß et al. (2014) defines systemic risk as the risk of contagion from one bank that defaults to the banking industry, and the contagion from one bank that defaults to all listed companies as systematic risk.
[124] According to Laeven et al. (2016), CoVar is defined as the Value at Risk (VaR) of the market return of the portfolio of all financial firms conditional to an event occurring to one of the banks; SRisk, is a

large banks in periods of financial distress. Altunbas et al. (2017) use the Marginal Expected Shortfall (MES), proposed by Acharya et al. (2017), as a measure of systemic risk, and find that larger banks, with aggressive credit policy and funded by unstable sources before the financial crisis explain systemic risk during the financial crisis.

The financial crisis of 2007-2009 also stimulated research on the systematic and idiosyncratic components of bank risk. Bessler and Kurmann (2014) adopt a multi-factor approach to analyse the sensitivity of bank stock returns of the US and European commercial banks from 1990 to 2011 to systematic risk. They show that banks are more exposed to systematic risk during financial distress and find that US banks' stock return variance is mainly explained by the high exposure to real state and exchange risk, while for European banks the sovereign risk is highly significant after the European sovereign debt crisis. Bessler et al. (2015) examine the systematic and idiosyncratic risk exposures of US bank holding companies from 1986 to 2012 and find that the systematic risk[125] exposures explain more than 70% of the stock returns variance. Moreover, the analysis of the drivers of the idiosyncratic risk shows that higher capitalization and profitability decreases the risk exposure, while a higher ratio of loan-loss provisions increases it. Bank size is not a significant determinant in their study.

6.2.2 The interdependence of sovereign risk and bank risk

The link between sovereign risk and bank risk is well established in the literature. Correa and Sapriza (2014) note that banks and sovereigns have a strong connection during periods of distress. For instance, when a banking crisis occurs, the government is expected to act as a guarantor on banks' liabilities, which can stress the governments' own solvency. On the contrary, a sovereign crisis can also turn into a bank crisis. BIS (2011) notes that there are four channels of transmission. First, through the banks' portfolio holdings of public securities, which under sovereign distress can constrain banks' liquidity. Second, through a collateral/liquidity channel, which happens if public debt is used as banks' collateral and the sovereign experience distress. Third, through a rating channel, as sovereign rating downgrades can increase the costs of funding through the bond or equity market. Fourth, through

measure of the expected capital shortage that could be faced by a financial firm during a period of system distress.

[125] The systematic bank risk, by Bessler et al. (2015), includes: interest risk, credit risk, sovereign risk and real state risk.

government guarantees, which occurs when a sovereign crisis reduces the state's capability to provide financial support to banks, which increases the banks' funding costs.

Williams et al. (2013) examine the rating channel from sovereign ratings to bank ratings in emerging economies. They show that sovereign rating upgrades (downgrades) significantly influence bank rating upgrades (downgrades), and banks at the sovereign ceiling[126] are more sensitive to sovereign rating actions. Moreover, the analysis of each GRA shows that the risk assessment of the effect of the sovereign rating actions on the bank rating actions varies between GRAs. For instance, the probability of taking a bank rating action after a sovereign rating action is higher for Fitch than for the other two GRAs. Moreover, the likelihood that Moody's and S&P take bank rating actions after a sovereign rating action is higher when the bank is located in a country with the lowest sovereign rating. Alsakka et al. (2014) examine the rating channel in European banks, before and during the European debt crisis, and show that sovereign rating downgrades and negative CreditWatch have a significant impact on bank rating downgrades during the crisis period. Their analysis shows that the effect of sovereign rating actions on bank rating actions differs between GRA. For instance, the likelihood of S&P downgrading the bank after a sovereign downgrade is higher than for Moody's and Fitch sovereign downgrades.

Huang and Shen (2015) examine the rating channel for S&P and Fitch, considering banks in high-income and non-high-income countries. They find that the sovereign effect is stronger in non-high-income countries and that the influence of sovereign downgrades on bank ratings is stronger than the effect of sovereign rating upgrades. Also, they show that banks rated equal or higher than the sovereign rating are strongly influenced by sovereign rating changes, while banks below the sovereign ceiling are more influenced by their holdings of public debt than directly by sovereign rating changes. However, for S&P, the argument of public debt holding only holds for high-income countries, while for Fitch the results are significant for both high-income and non-high-income countries.

Williams et al. (2015) examine three transmission channels from sovereign risk to bank risk in bank stock valuations in emerging economies. They show that sovereign ratings have a strong effect on bank valuations (rating channel) through new information ratings,[127] negative

[126] Banks that are rated at the same level as the sovereign are called "banks at the sovereign ceiling" by Williams et al. (2013).
[127] Williams et al. (2015) defines new rating information as a credit event which follows the contrary path as the past rating (positive rating action following a negative rating action or vice versa) by any of

outlooks and CreditWatch, although the effect differs between GRAs. In contrast, they find a weak effect of the collateral channel (measured by the sovereign rating level) and the guarantee channel (measured by the ratio of governments' debt to GDP) on bank valuations, although both channels are more relevant in banks from countries that received sovereign upgrades. However, they show that the rating channel varies for each GRA. For instance, positive (negative) new information ratings are more significant for S&P and Fitch (Moody's and Fitch). Moreover, the effect of S&P sovereign rating upgrades on bank valuations is more significant in countries where the government has stronger control over the financial system.

Adelino and Ferreira (2016) argue that the sovereign ceiling effect increases the negative effect of a sovereign downgrade in banks with ratings equal to the sovereign (treatment group), compared to banks that have ratings below the sovereign rating (non-treatment group). Owed to sovereign downgrades, banks in the treatment group face a higher cost of funding and reduce their lending. Drago and Gallo (2017) analyse the effect of sovereign rating changes by S&P on the activity of European banks from 2004 to 2016. They find that sovereign actions, particularly downgrades, influence banks' activity through three channels, as follows. First, sovereign rating downgrades affect capital ratios through its negative impact on the banks' risk-weighted assets (asset channel). Second, they impact lending supply by limiting the access to short-term funding (funding channel). Third, they have a stronger impact on the capital in banks rated at or above the sovereign ceiling (rating channel). They also show sovereign rating changes influence bank financial fundamentals through the "certification effect". Namely, when calculating minimum capital requirements, Basel II and III require that the sovereign risk is incorporated in the risk weights if the bank holds public debt (BIS, 2013).

6.2.3 Government transparency and bank risk in emerging economies

Information asymmetries and weak institutional environment are common features of emerging economies. Vu et al. (2017) examine the causes of sovereign rating disagreements in European and non-European emerging economies from 1997 to 2011. They find that political risk and information disclosure quality has a significant effect on split sovereign ratings in emerging economies.

---

the three GRAs, or a credit event by one of the GRAs which reduces (increases) the rating to a lower (higher) level than the lowest (highest) level assigned by any of the other two GRAs.

Previous literature shows that the government opacity has a strong influence on bank risk. For instance, government corruption has a negative impact on bank lending and the effect is much stronger in countries where the level of corruption is higher (Weill, 2011b, 2011a; Park, 2012). Moreover, there is evidence that the banks' risk-taking behaviour is significantly influenced by the corruption level in emerging economies, after controlling for the effects of bank characteristics, public policies and the macroeconomic environment of the countries (Chen et al., 2015). Higher levels of corruption also have a strong impact on bank stability in emerging economies (Toader et al., 2018). Thakur and Kannadhasan (2019) find a significant positive relation between corruption and cash holdings in emerging economies, suggesting that financial institutions hold more liquidity because they benefit from the corruption environment. However, when the country is highly corrupt, they find that holding cash does not have an advantage.

6.2.4 Concluding remarks

Bank crisis can generate contagion effects on the economy. An increase of the banks' risk-taking behaviour and their strong interconnectedness with the rest of the economic sectors, explain the high probability of contagion. Literature shows that, among the sources of bank risk exposure, sovereign risk is a significant source of systematic risk. This Chapter does not examine the systematic risk component in bank risk, as implied by the asset pricing model. Yet, this Chapter uses the same principle of dividing the factors that explain split bank ratings into idiosyncratic factors, which proxy the bank's opacity (and are studied in Chapter 5), and potential systematic factors, which are external factors that can influence CRAs' disagreements about bank ratings.

One channel of transmission of sovereign risk to the banking industry is the rating channel, which shows that sovereign rating actions have an important effect on bank rating actions. Moreover, studies show that bank rating actions are more sensitive to sovereign rating actions when the ceiling effect takes place, suggesting that the effects of the sovereign ceiling are stronger in emerging economies. Despite the significant evidence of the transmission of the sovereign risk to bank risk through the rating channel, sovereign risk has not been incorporated in studies of split bank ratings. As research suggests that sovereign opacity is much more significant in emerging economies and that government corruption increases bank-risk taking behaviour, the study of the transmission of sovereign risk to bank risk through split bank ratings is especially relevant in these economies. Thus, this Chapter fills a clear void in the literature by examining whether split sovereign ratings represent the systematic factor that explains the probability of split bank ratings and investigating the impact of the sovereign ceiling on bank rating disagreements. Hence, Chapter 6 offers a different viewpoint of the rating channel for transmission of the sovereign risk to bank risk.

6.3 Research question and hypothesis development

The results in Chapter 5 support the opacity theory proposed by Morgan (2002) and Livingston et al. (2007). The literature on the drivers of split bank ratings, however, is silent on the influence of sovereign risk on bank rating disagreements, despite the evidence of the strong link between sovereign risk and bank risk through the rating channel (see Section 6.2.2). Thus, this Chapter examines the rating channel of transmission of sovereign risk to bank risk from a perspective of rating disagreements between GRAs. Thus, while the focus of Chapter 5 is on the idiosyncratic factors (bank-specific factors) that drive bank splits, Chapter 6 examines whether sovereign opacity, proxied by split sovereign ratings, is a systematic factor that influence bank split ratings. Sovereign split ratings are considered as signals of the uncertainty regarding the probability of default of a sovereign (Vu et al., 2015). Thus, the first research question of this Chapter investigates whether split sovereign ratings influence split bank ratings and if they can be considered the systematic component of split bank ratings in emerging economies. Bessler et al. (2015) show that sovereign risk has a significant influence on the systematic risk of European banks. Therefore, the first hypothesis of the study is:

Hypothesis I: *Split sovereign ratings have a strong influence on split bank ratings in emerging economies. Thus, they can be considered as the systematic component of GRAs' bank rating disagreements.*

Previous literature shows that when split ratings occur, one of the GRAs tends to assign lower ratings than the other. Morgan (2002) shows that Moody's tends to assign ratings in a more conservative manner than S&P, when bank rating disagreements occur. He shows that the lopsided ratings are more pronounced in opaque sectors, where the conservative GRA behaves even more cautious due to higher uncertainty. Livingston et al. (2010) test the lopsided behaviour of ratings in corporate bonds with split ratings between S&P and Moody's. They find that Moody's is the most conservative GRA and that split-rated bonds with superior ratings by Moody's tend to have lower yields than split-rated bonds with inferior ratings by the Moody's. Vu et al. (2015) show that the lopsided behaviour in sovereign ratings has a significant effect on the market response to sovereign rating actions through the sovereign bond spreads. Vu et al. (2017) find evidence of lopsided ratings from S&P when analysing split sovereign ratings in European and non-European emerging economies. Considering the evidence of lopsided rating behaviour in banks and sovereign ratings, the second research question examines if the tendency to assign lower sovereign ratings is transmitted to bank ratings. Thus, a second hypothesis is as follows:

Hypothesis II: *When the sovereign has split ratings, and one GRA tends to assign lower sovereign ratings than the other GRA, the tendency to assign lower ratings will be observed also in bank ratings.*

Additionally, the literature on corporate ratings shows that issuers (or issues) rated equal or above sovereign ratings prior to a sovereign downgrade are more likely to be downgraded after sovereign rating downgrades, compared to issuers (or issues) which have ratings below the sovereign ratings (Almeida et al., 2017). For bank ratings, Williams et al. (2013) find that banks rated at the same or higher level as the sovereign are more sensitive to changes in sovereign ratings than banks with ratings lower than the sovereign ratings. Furthermore, Huang and Shen (2015) provide evidence of the prevalence of the ceiling effect over bank fundamentals when GRAs (S&P and Fitch) assign bank ratings in non-high-income countries (NHIC).[128] They also show that S&P reacts differently to the ceiling effect than Fitch. Thus, motivated by the role of the sovereign ceiling on bank ratings, the third question examines whether the effect of sovereign rating disagreements on split bank ratings is stronger when the ceiling effect takes place. Thus, the third hypothesis is as follows:

Hypothesis III: *The ceiling effect increases the sensitivity of split bank ratings to split sovereign ratings.*

In summary, the hypotheses address three main issues: the probability or sensitivity of split bank ratings to split sovereign ratings, the lopsided behaviour in bank ratings related to split sovereign ratings and the impact of the sovereign ceiling on bank rating disagreements.

[128] The non-high-income countries (NHIC) definition used by Huang and Shen (2015), follows the World Bank classification of countries according to the GNI per capita. This Chapter also studies sovereign ratings in NHIC, namely: Argentina, Brazil, China, Colombia, Indonesia, Kazakhstan, Mexico, Nigeria, Russia, South Africa, and Thailand.

6.4 Data

6.4.1 Rating data

The study employs quarterly long-term foreign-currency issuer and sovereign credit ratings from October 2008 to December 2015, for issuers domiciled in 11 emerging economies. The sampled countries and the period of analysis are selected based on the financial data availability in Bankscope database. The countries are: Argentina, Brazil, China, Colombia, Indonesia, Kazakhstan, Mexico, Nigeria, Russia, South Africa, and Thailand. The dataset is built from the data collected for Chapter 4 from Interactive Data Credit Ratings in Emerging Markets (Henceforth, ID-CREM) and CapitalIQ. For the current Chapter, only banks with quarterly ratings assigned by at least two of the three GRAs are used.[129]

Following Alsakka and ap Gwilym (2010a), the credit rating scale of each GRA is transformed into an 18-point[130] numerical scale (see Section 5.4.1 for more details). Quarterly rating disagreements correspond to notch differences between each pair of GRAs. Table 6.1 reports the quarterly rating data by each pair of GRA. It comprises: 1,898 observations for 92 banks from 9 countries[131] rated jointly by S&P and Moody's; 1,767 observations for 90 banks from 10 countries[132] rated jointly by S&P and Fitch; and 2,423 observations for 111 banks from 10 countries[133] rated jointly by Moody's and Fitch.

The sample presents a high proportion of bank rating disagreements: S&P and Moody's (74.7%), Moody's and Fitch (69.3%), and S&P and Fitch (54.4%).[134] The proportion of sovereign rating splits is also high: S&P and Moody's (61.6%), Moody's and Fitch (67.4%) and S&P and Fitch (39.5%). Alsakka and ap Gwilym (2010b) examine sovereign split ratings

[129] While Chapter 4 incorporates in the analysis the ratings at the national rating scale by S&P collected from ID-CREM, the current Chapter (as Chapter 5) uses only global scale ratings from the three GRAs collected from ID-CREM.
[130] Following the approach used by Alsakka and ap Gwilym (2010a), the credit rating scale of each GRA is transformed into numerical scale. Since the current Chapter employs the GSR from S&P, Moody's and Fitch, and Fitch does not use modifiers "+" or "-" in the categories CCC (value of 2 in the numerical scale) or below, the ratings are transformed into an 18-point numerical scale instead of the 20-point numerical scale used in Chapter 4 where only S&P ratings are used.
[131] Argentinean banks are excluded since they are not rated by both S&P and Moody's, Nigerian banks are removed from the sample rated by S&P and Moody's as they have only one observation during the period of analysis.
[132] Argentinean banks are excluded since they are not rated by both S&P and Fitch.
[133] Nigerian banks are removed from the sample rated by Moody's and Fitch as they have only one observation during the period of analysis.
[134] As the sampled banks can have ratings from two or three GRAs, it is possible that the same bank has split ratings from different pairs of GRAs.

in emerging economies for the earlier period of 2000 – 2008 and find similar percentages of sovereign rating disagreements for S&P and Moody's (59.4%) and for S&P and Fitch (34.6%). However, the proportion of disagreements between Moody's and Fitch is lower than in the current study (57.6%). The majority of split bank ratings and split sovereign ratings are of one notch for each pair of GRAs. Split ratings of three or more notches are scarce. The highest number of one-notch split bank ratings is reported for Moody's and Fitch, followed closely by S&P and Moody's.

6.4.2 Split bank ratings and split sovereign ratings

The objective of Chapter 6 is to study the sensitivity of split bank ratings to government opacity and the ceiling effects (the systematic factors) in emerging economies. Literature shows that government opacity can be measured through different economic indicators. Chen et al. (2015) use the corruption index, calculated by Transparency International and by the World Bank (this variable is also used in Chapter 4 as control variable), as a proxy of government transparency. Shen et al. (2012) include an indicator of law and order tradition and level of bureaucracy as proxies of the quality of the institutional environment. Finally, Vu et al. (2017) use two variables as proxies of government opacity: i) an indicator of the governments' quality of information disclosure to the public,[135] and ii) an indicator of political risk, using the Worldwide Governance Indicators (WGI) estimated by the World Bank[136]. Vu et al. (2017) show that split bank ratings incorporate the GRAs' evaluation of the corruption level, the institutional quality, the quality of public information and the regulatory framework, among other factors. Since these aspects are evaluated independently by each measure proposed by Shen et al. (2012) and Chen et al. (2015), it is reasonable to consider that split sovereign ratings are a comprehensive measure of government opacity. Therefore, sovereign split ratings are selected as the proxy of government opacity in the current Chapter.

To minimize potential endogeneity concerns on omitted variables, the estimations incorporate country and year fixed effects. Nonetheless, there might be variables that are omitted which could be interesting for the particular examination of GRAs' bank rating disagreements. For instance, Williams et al. (2013) argue that in countries with stronger economic, financial and

[135] Vu et al (2017) obtain the information on the quality of information disclosure from "Overview of all FOI laws" report by Vleugels (2011).

[136] According to Vu et al (2017), the World Governance Indicators (WGI) evaluate six aspects of governance: Voice and Accountability, Political Stability and Absence of Violence, Government Effectiveness, Regulatory Quality, Rule of Law and Control of Corruption.

business freedom,[137] bank ratings are less sensitive to changes in the sovereign ratings. The economic freedom index by the Heritage Foundation used in Williams et al. (2013) could be covering aspects that are not explicitly measured by split ratings directly, such as the market openness, which addresses aspects of investment, trading and financial freedom that might be drivers of split bank ratings.

Table 6.2 presents the number of observations where one GRA assigns lower or higher ratings than the other GRA when split bank (or sovereign) ratings occur. In split bank ratings, S&P assigns ratings in a more conservative manner than Moody's and Fitch, assigning inferior ratings in 80.7% and 78.1% of the split bank ratings observations, respectively. For split bank ratings between Moody's and Fitch, Fitch assigns lower ratings than Moody's in 58.8% of the split bank ratings observations. In split sovereign ratings, S&P also assigns lower ratings than Moody's (Fitch) in 90.2% (62.6%) of the split sovereign ratings observations. For Fitch and Moody's, Fitch assigns inferior sovereign ratings in 88.9% of the observations with split ratings. In sum, the descriptive statistics show that those GRAs that tend to assign sovereign ratings in a more conservative manner, have the same behaviour when bank ratings disagreements occur.

Further analysis on split bank ratings and split sovereign ratings is presented in Figure 6.1. The figure shows that split bank ratings and split sovereign ratings follow similar behaviour, supporting the hypothesis of a systematic link between split bank ratings and sovereign split ratings. The number of observations whereby S&P assigns inferior bank or sovereign ratings than Moody's (Figure A) and Fitch (Figure C), are higher than when S&P assigns a superior rating than Moody's (Figure B) and Fitch (Figure F). Moreover, Figures B and C show an upward tendency of the number of observations where S&P assigns superior banks and sovereign ratings after the financial crisis of 2007-2009 until the end of 2013. In contrast, from 2014 there is a sharp increase in the number of observations where S&P assigns lower ratings for sovereigns and banks compared to Moody's and Fitch. Moody's shows the same sharp increase in 2015 compared to Fitch (Figure E). The behaviour of S&P might be related to the taper tantrum,[138] which generated volatility in emerging economies (Sahay et al., 2014), the

[137] Williams et al (2013) use the economic freedom index estimated by the Heritage Foundation and each of its 10 elements of economic freedom separately: Financial, investment, trade, fiscal, government spending, business, monetary, labour and rule of law: property rights and freedom from corruption.

[138] The taper tantrum refers to the relaxation of the bond-buying program and tightening of the monetary policy of the U.S. Federal Reserve (Sahay et al., 2014).

GRAs' perception of higher default risk probability of some emerging economies such as Brazil and China (Moody's, 2015a), and the effect of the crisis in Ukraine on Russia (Moody's, 2015b).

6.4.3 Evidence of the ceiling effect

Table 6.3 presents the percentage of bank rating observations equal to or above the sovereign ratings (i.e. ceiling effect). The concept of the ceiling effect follows the literature, which shows that bank ratings at or above the sovereign rating are more sensitive to sovereign rating actions (e.g. Williams et al., 2013; Huang and Shen, 2015; Adelino and Ferreira, 2016; Almeida et al., 2017). For banks with split ratings, Fitch has the highest number of observations with bank ratings equal or above the sovereign ratings compared to S&P and Moody's. Namely, when banks are rated by S&P and Fitch, 49.3% (47%) of Fitch (S&P) bank ratings are at the same level or higher than the sovereign rating. For banks rated by Moody's and Fitch, 39.7% (49.9%) of the bank ratings by Moody's (Fitch) are equal or higher than the sovereign rating. For banks jointly rated by S&P and Moody's, 41% (39%) of the split observations have S&P (Moody's) bank ratings have the same or higher level than the sovereign ratings.

The percentages of split bank ratings are in line with Huang and Shen (2015), who report for banks from non-high-income countries rated by S&P and by Fitch, that 50.2% of bank ratings are equal or better than the sovereign, for the period 2003-2011. In contrast, Williams et al. (2013) report for banks in emerging economies rated by S&P, Moody's or Fitch from November 1999 to December 2009, that 65.5% (10.8%) of the bank ratings have the same (higher) rating than the sovereign. The percentages in Williams et al. (2013) compared to the percentages presented in this Chapter indicate a fall in the number of bank ratings at or above the sovereign ceiling. This could be suggesting that, after the financial crisis of 2007-2009, GRAs are more cautious of assigning bank ratings at or above the sovereign rating, considering that sovereign downgrades can lead to bank downgrades, and in turn those downgrades can cause financial stress and affect the real economy. Figure 6.3 presents the history of the sovereign ratings of each sampled country and of the average bank ratings for the sampled banks. The figures confirm that the largest percentage of bank ratings are equal or below the sovereign ratings in all the sampled countries. Only Kazakhstan presents bank rating below the sovereign rating in all the period of analysis. In summary, the univariate analysis of the data suggest that the ceiling effect plays a relevant role in split bank ratings from emerging economies.

6.5 Methodology

6.5.1 Systematic component of split bank ratings

To investigate the influence of split sovereign ratings as the selected systematic factor that could impact split bank ratings, an ordered probit modelling approach is employed for each of the three pairs of GRAs. Ordered response models are appropriate when considering the discrete and ordinal nature of the data (Greene, 2012), in this case, rating differences. These type of models are commonly used in split ratings literature (e.g. Morgan, 2002; Iannotta, 2006; Livingston et al., 2007; Alsakka and ap Gwilym, 2012). For the investigation, cases where GRA1 assigns superior ratings are separated from cases where GRA1 assigns inferior ratings. These separation follows the credit rating literature, which shows that one GRA tends to assign inferior or lower ratings when split ratings occur (Morgan, 2002; Iannotta, 2006; Livingston et al., 2010; Alsakka and ap Gwilym, 2012; Bowe and Larik, 2014; Vu et al., 2017). The specification of the model for split ratings where GRA1 assigns a superior rating is as follows:

$$BSSup^{*}_{i,j,t} = \beta_1 SSInf_{j,t} + \beta_2 SSup_{j,t} + \delta YD + \phi CD + \varepsilon_{i,j,t} \tag{6.1}$$

Additionally, for split ratings where GRA1 assigns an inferior rating, the specification is as follows:

$$BSInf^{*}_{i,j,t} = \beta_1 SSInf_{j,t} + \beta_2 SSup_{j,t} + \delta YD + \phi CD + \varepsilon_{i,j,t} \tag{6.2}$$

$BSSup^{*}_{i,j,t}$ and $BSinf^{*}_{i,j,t}$ are unobserved latent variables linked to the observed ordinal response categories $BSSup_{i,j,t}$and $BSInf_{i,j,t}$ by the measurement models:

$$BSSup_{i,j,t} = \begin{cases} 0\ (i.e. non - split\ ratings) & , \quad if\ BSSup^{*}_{i,j,t} \leq \mu_1 \\ 1\ (i.e. one - notch\ superior\ bank\ rating\ by\ GRA1) & , \quad if\ \mu_1 < BSSup^{*}_{i,j,t} \leq \mu_2 \\ 2\ (i.e. two\ or\ more\ notches\ superior\ bank\ rating\ by\ GRA1) & , \quad if\ \mu_2 < BSSup^{*}_{i,j,t} \end{cases}$$

$$BSInf_{i,j,t} = \begin{cases} 0\ (i.e. non - split\ ratings) & , \quad if\ BSInf^{*}_{i,j,t} \leq \mu_1 \\ 1\ (i.e. one - notch\ inferior\ bank\ rating\ by\ GRA1) & , \quad if\ \mu_1 < BSInf^{*}_{i,j,t} \leq \mu_2 \\ 2\ (i.e. two\ or\ more\ notches\ inferior\ bank\ rating\ by\ GRA1) & , \quad if\ \mu_2 < BSInf^{*}_{i,j,t} \end{cases}$$

Where μ_m denote thresholds, subject to the constraint that $\mu_1 < \mu_2$. The subscripts i, j, t denote bank, country and time (quarters), respectively. The variable $BSSup$ ($BSInf$) denotes split bank ratings (of one-notch or two-or-more-notches), where GRA1 assigns superior (inferior) bank ratings than GRA2. Eq. (6.1) and (6.2) are estimated for each pair of GRAs.[139] $SSup$ is a

[139] There are three pairs of GRAs: S&P and Moody's, S&P and Fitch and Moody's and Fitch. For split ratings between S&P and Moody's, GRA1 corresponds to S&P. For split ratings between S&P and Fitch, GRA1 is S&P. For split ratings between Moody's and Fitch, GRA1 is Moody's.

dummy variable that takes the value of one when GRA1 assigns superior sovereign ratings than GRA2. $SSInf$ is a dummy variable that takes the value of one when GRA1 assigns inferior sovereign ratings than GRA2.

To partial out country-level time-invariant unobserved effects and control for time shocks that might affect the banks in the sample, Eqs. (6.1) to (6.4) incorporate a set of year (*YD*) and country dummy variables (*CD*). Any concerns on heteroscedasticity and serial correlation in the error terms of all equations are addressed by using Huber-White heteroskedasticity standard errors (for further details on fixed effects and robust errors, see Section 4.5.1).[140] Marginal effects (MEs) are estimated holding all other variables constant at their sample means (MEM), only for variables with significant (at 5% or better) coefficients. The rationale for incorporating MEs in probit estimations is detailed in Section 4.5.1.

6.5.2 Ceiling effect

Williams et al. (2013) find that bank ratings equal to or above the sovereign ratings are more sensitive to sovereign rating actions. Almeida et al. (2017) show that corporates that have ratings at the same level or higher than the sovereign rating (bounded firms) are more likely to be downgraded than corporates with ratings below the sovereign rating (non-bound firms). To incorporate the "ceiling effect", two dummy variables: *CeGRA1* and *CeGRA2* are added to Eqs. (6.1) and (6.2). *CeGRA1* and *CeGRA2* capture whether the bank rated by GRA1 (or GRA2) is bounded by the sovereign ceiling effect. To investigate if the effect of sovereign split ratings on split bank ratings can differ when the ceiling effect takes place, Eq. (6.3) and (6.4) are also estimated with the interaction terms between the sovereign split dummy variables ($SSup$ or $SSInf$) and the ceiling dummy variables (*CeGRA1* or *CeGRA2)*. The following models are estimated:

$$BSSup^*_{i,j,t} = \beta_1 SSInf_{j,t} + \beta_2 SSup_{j,t} + \beta_3 CeGRA1_{i,j,t} + \beta_4 CeGRA2_{i,j,t} + \beta_5 CeGRA1_{i,j,t} * SSInf_{j,t} + \beta_6 CeGRA1_{i,j,t} * SSup_{j,t} + \beta_7 CeGRA2_{i,j,t} * SSInf_{j,t} + \beta_8 CeGRA2_{i,j,t} * SSup_{j,t} + \delta YD + \phi CD + \varepsilon_{i,j,t} \quad (6.3)$$

For split ratings where GRA1 assigns a lower rating, the specification is as follows:

[140] While not reported in the study, Eqs. (6.1) to (6.4) are also estimated using clustered standard errors at the bank level, and similar results are obtained.

$$BSInf^{*}_{i,j,t} = \beta_1 SSInf_{j,t} + \beta_2 SSup_{j,t} + \beta_3 CeGRA1_{i,j,t} + \beta_4 CeGRA2_{i,j,t} + \beta_5 CeGRA1_{i,j,t} * SSInf_{j,t} + \beta_6 CeGRA1_{i,j,t} * SSup_{j,t} + \beta_7 CeGRA2_{i,j,t} * SSInf_{j,t} + \beta_8 CeGRA2_{i,j,t} * SSup_{j,t} + \delta YD + \phi CD + \varepsilon_{i,j,t} \quad (6.4)$$

The subscripts i, j, t denote bank, country and time (quarters), respectively. The definition of $BSSup^{*}_{i,j,t}$ and $BSinf^{*}_{i,j,t}$ are the same as Eqs. (6.1) and (6.2). *CeGRA1* is a dummy variable that takes the value of one when the bank rating is equal or superior to the sovereign rating assigned by GRA 1. *CeGRA2* takes the value of one when the bank rating is equal or superior to the sovereign rating assigned by GRA 2. The reference category for *CeGRA1 (CeGRA2)* are the cases where bank ratings assigned by GRA1 (GRA2) are inferior to sovereign ratings assigned by GRA1 (GRA2). The estimations of Eqs. (6.3) and (6.4) including the ceiling dummy variables are reported in Tables 6.5 to 6.10, while the estimations of Eq. (6.3) and (6.4) including the ceiling dummy variables and the interaction terms[141] are reported in Tables A 6.1 to A 6.6 in the Appendix[142].

For statistically significant regressors (at 5% or better), marginal effects (MEs) at their mean value are estimated, holding all other variables constant at their sample means (MEM). The rationale for incorporating MEs in the estimations of Eqs. (6.1) to (6.4) is detailed in Section 4.5.1. The MEs of the interaction terms for Eqs. (6.3) and (6.4) are estimated at each level of the other covariate, concerning the probabilities of the outcome 1 and 2 (see Tables A 6.1 to A 6.6 in the Appendix). The MEs of the interactions are estimated for split bank ratings of one-notch and two-or-more-notches (outcomes 1 and 2). The MEs reported in Tables A 6.1 to 6.6 in the Appendix are: (i) when the GRA assigns an inferior (superior) sovereign rating and the ceiling effect applies, and (ii) when the GRA assigns an inferior (superior) sovereign rating and there is no ceiling effect.

6.5.3 Expected signs of the coefficient estimates - Eq. (6.1) to (6.4)

Table 6.4 presents a summary of the variables used in Eqs. (6.1) to (6.4) and the expected sign of the coefficients. Regarding $SSup$ and $SSInf$, research shows that split sovereign ratings are

[141] In some estimations of Eqs. (6.3) and (6.4), it appears that some interacted covariates predict one of the outcomes perfectly. Therefore, Eqs. (6.3) and (6.4) are estimated without some of the interaction terms. These include: SSInf*CeM, SSup*CeM, SSup*CeSP (Table A 6.1); SSInf*CeF and SSup*CeF (Table A 6.2); SSInf*CeM (Table A 6.3); SSup*CeSP, SSup*CeM (Table A 6.4); SSup*CeSP (Table A 6.5); SInf*CeM (Table A 6.6).
[142] The interaction effects are reported in the Appendix of Chapter 6 due to the limited space and the significant number of tables presented in Chapter 6.

a measure of the political risk and information opacity in emerging economies (Vu et al., 2017). Considering that lack of government transparency increases the bank's risk-taking behaviour (Chen et al., 2015), split sovereign ratings, as a measure of ambiguity on the government transparency, should represent higher uncertainty in the banking sector. Furthermore, Chapter 5 and earlier research shows that when split sovereign ratings occur, one of the GRAs tends to assign inferior ratings (Alsakka and ap Gwilym, 2012; Vu et al., 2015, 2017). If split sovereign ratings reflect the uncertainty of the GRAs on the sovereigns' probability of default, and one GRA worries about overrating the sovereign (the most conservative), the same tendency to assign lower ratings would be expected in bank ratings, considering the significant influence of sovereign risk on bank risk. Thus, for the cases where GRA1 assigns inferior bank ratings, $SovSInf$ and $SovSSup$ are expected to have a positive and negative sign, respectively. On the contrary, for cases where GRA1 assigns superior bank ratings, $SSInf$ and $SSup$ are expected to have a negative and positive sign, respectively.

Regarding the *CeGRA1* and *CeGRA2*, previous literature shows that the banking industry is more opaque than other industries (Morgan, 2002; Iannotta, 2006; Dahiya et al., 2017; Fosu et al., 2018). In emerging economies, previous research shows that a lack of government transparency increases the risk-taking behaviour in banks (Chen et al., 2015). Following the literature, in emerging economies, the probability of split bank ratings should be higher when the ceiling effect occurs, because banks with ratings equal or higher than the sovereign are more sensitive to sovereign risk (see Williams et al., 2013). However, a GRA assigns bank ratings equal to or higher than the sovereign because it has a positive perception of the banks' baseline credit assessment.[143] Therefore, when split ratings occur, the GRA that assigns bank ratings at the same or above the level of the sovereign rating should be less (more) likely to assign inferior (superior) bank ratings than the competitor GRA. Hence, *CeGRA1* should have a positive (negative) sign when GRA1 assigns a superior (inferior) bank rating. For *CeGRA2* the opposite signs are expected.

The sensitivity of bank rating changes to sovereign rating changes when the ceiling effect takes place, which is found in the literature, indicates that when GRA1 assigns inferior (superior) sovereign ratings and the ceiling effect applies, the coefficient of the interaction term: $SovSInf$*CeGRA1* should be positive (negative). Thus, when the ceiling effect applies, inferior sovereign ratings assigned by GRA1 should increase (decrease) the likelihood of GRA1

[143] Baseline credit assessments (BCA) refers to the GRAs' credit opinion of the issuers standalone creditworthiness without considering parent or sovereign support (Moody's, 2019b).

assigning lower (higher) bank ratings. In contrast, the coefficient of *SovSup*CeGRA1* should be negative (positive) when GRA1 assigns inferior (superior) bank ratings. The interpretation is that when bank ratings are the same or exceed the sovereign ceiling, the probability of assigning an inferior (superior) bank rating should decrease (increase) if GRA1 assigns superior sovereign ratings. The effects of GRA2 should be the opposite of that for GRA1.

6.6 Empirical results

This section examines the sensitivity of split bank ratings to split sovereign ratings and the effect of the sovereign ceiling on GRAs' bank rating disagreements. Overall, the results suggest that both split sovereign ratings and the ceiling effect are systematic factors explaining split bank ratings, as the Pseudo-R^2 of the models improves when both types of dummy variables are included. The probabilities of inferior bank ratings are more sensitive than superior bank ratings to split sovereign ratings and to the sovereign ceiling dummies. Particularly, split sovereign ratings and the ceiling effect seem to have the strongest effect on the probabilities of S&P inferior bank ratings than Fitch. The estimations also show that split sovereign ratings dummy variables and the ceiling effect dummy variables have higher economic significance for one-notch split bank ratings than for two-or-more notches split bank ratings. These results are driven by the significant number of split ratings observations with one-notch compared to two-or-more notches (see Table 6.2). There is an exception, as the probability of S&P two-notches inferior bank ratings than Moody's is more sensitive to split sovereign ratings than S&P one-notch inferior bank ratings. The latter result suggests that split sovereign ratings between S&P and Moody's signal a greater uncertainty to their bank ratings compared to the other pair of GRAs.

In the estimations that include the interaction terms between the split sovereign dummies and the sovereign ceiling dummies (Tables A 6.1 to A 6.6), all the coefficients of the interaction terms are statistically significant. In these results, the main variables (*SSup*, *SSInf*, *CeGRA1*, and *CeGRA2*) are consistent with the results reported in the main tables (Tables 6.5 to 6.10), although in some cases, the latter variables are not significant.[144] The interaction effects show that split bank ratings are more sensitive to split sovereign ratings when the sovereign ceiling takes place, for all pairs of GRAs. Also, the coefficient of the ceiling effect of the competitor GRA is highly significant in the inferior bank rating cases (Tables A 6.4 to A 6.6) and shows a stronger impact on bank splits of two-or-more-notches.

[144] The main variables that are no longer significant are: *SSInf* in Table A 6.2, *SSup* in Table A 6.3, *SSup* in Table A 6.5, *SSInf* in Table A 6.6. This results are not a concern in the Chapter because the interaction effects are always significant and the outcome on the main variables just shows that when the main variable = 0, the difference between groups is insignificant, while the difference might be significant if the main variable is different from zero (see Williams, 2015). The literature on sovereign ratings and bank opacity that includes interactions also reports the significance of the interactions, despite the lack of significance of some of the main variables (see Almeida et al., 2017; Blau et al., 2017).

6.6.1 Higher bank ratings from GRA1

Table 6.5 reports the results of the estimations of Eqs. (6.1) and (6.3) for split bank ratings between S&P and Moody's, with superior S&P ratings. Sovereign split ratings are not significant in Eq. (6.1).[145] In comparison, when the ceiling effects are added (Eq. 6.3), the coefficient of inferior S&P sovereign ratings (*SSInf*), is significant and with the expected negative sign. Both coefficients of the proxies of the ceiling effect[146] (*CeSP* and *CeM*) are also statistically significant and have the expected positive and negative signs, respectively. Eq. (6.3) shows that the probability of S&P assigning one-notch (two-or-more notches) superior bank ratings than Moody's decreases by 17% (5%) when S&P sovereign ratings are inferior than Moody's sovereign ratings (*SSInf*). Moody's ceiling effect (*CeM*) has a stronger impact on the probabilities of split bank ratings than S&P ceiling effect (*CeSP*). Thus, when Moody's (S&P) bank ratings are equal or superior to Moody's (S&P) sovereign ratings, the likelihood of S&P assigning one-notch superior bank ratings than Moody's decreases (increases) by 38% (22%). In comparison, the probabilities of split bank ratings of two-or-more-notches are less sensitive to split sovereign ratings and the ceiling effect, which is explained by the higher proportion of S&P one-notch inferior ratings than Moody's (see Table 6.2). The Pseudo-R^2 value is higher for Eq. (6.3) than for Eq. (6.1), suggesting that the ceiling effect is an important systematic factor explaining split bank ratings between S&P and Moody's and that split bank ratings are highly sensitive to the competitors' sovereign ceiling.

Table A 6.1 in the Appendix reports the results for superior S&P bank ratings than Moody's. The results include the interaction between split sovereign and ceiling effect dummies. The coefficient of the interaction *SSInf*CeSP* is significant at 1% level and has the expected negative sign.[147] The MEs also show that the likelihood of two-or-more-notches higher S&P bank ratings is more sensitive to S&P inferior sovereign ratings when S&P ceiling effect

[145] The results of Eqs. (6.1) to (6.4) are unchanged when using an additional category (3) in the measurement model (see Section 6.5.2). Namely, instead of using 0, 1, 2 (where 2 is used for rating differences of two-or-more-notches), 2 would only include splits of two-notches and 3 would include splits of three-or-more notches. These results are not reported for brevity but are available on request.

[146] The ceiling effect is defined as a dummy that takes the value of one when the bank rating assigned by a GRA is equal or higher than the sovereign rating assigned by the same GRA.

[147] When including the interaction terms in Eq. (6.3), *SovSSup*CeilingSP*, *SovSSup*CeilingM*, and *SSInf*CeilingM* are dropped due to complete determination of the observations. Thus, the model only includes *SSInf*CeilingSP*. Because in all pairs of GRAs, complete determination of the observations is also evidenced for some of the interaction terms when superior and inferior bank rating assignments are examined, the explanation will not be repeated hereafter.

applies (decreases by 32%) than the likelihood of one-notch higher S&P bank ratings (increases by 1%).

Table 6.6 reports the results of the estimations of Eqs. (6.1) and (6.3) for split bank ratings, with superior S&P ratings than Fitch. Similar to S&P and Moody's, the split sovereign ratings dummy variables (*SSInf* and *SSup*) are only significant when including the ceiling effect dummy variables (Eq. 6.3). The probability of one-notch superior S&P ratings increases (decreases) by 21% (9%) if, during the same period, the sovereign has superior (inferior) S&P rating than Fitch. Thus, bank split ratings between these two GRAs are highly sensitive to the perception of uncertainty in the sovereign ratings. Moreover, if Fitch ceiling effect (*CeF*) occurs, it decreases the probability of S&P assigning one-notch superior bank ratings than Fitch by 38%, compared to an increase in the probability by 16% when S&P ceiling effect applies. These results suggest that the level of sovereign ratings assigned by the competitor GRA affects S&P bank rating decisions when the bank is jointly rated by S&P and other GRA.

Table A 6.2 in the Appendix reports the results for S&P superior bank ratings than Fitch. The coefficient of the interaction *SSup*CeSP* is positive and statistically significant at the 10% level. The interaction shows that the probability of assigning superior S&P bank ratings is more sensitive when S&P ceiling (*CeSP)* applies. Thus, the probability of one-notch (two-or-more-notches) higher S&P bank rating increases by 22% (21%) when S&P sovereign ceiling applies, and by 14% (9%) when there is no ceiling effect from S&P (*CeSP=0)*. In sum, the results from Tables A 6.1 and A 6.2 suggest that S&P sovereign ratings and S&P ceiling effect have a significant impact on S&P bank ratings for banks rated by S&P and Moody's or S&P and Fitch.

Table 6.7 presents the results of the estimations of Eqs. (6.1) and (6.3) for superior Moody's bank ratings than Fitch, with superior Moody's ratings. Unlike the previous pairs of GRAs, when split sovereign ratings occur and Moody's assigns inferior ratings (*SSInf*), the coefficient of *SSInf* is significant in Eq. (6.1). Namely, the probability of one-notch (two-or-more notches) superior Moody's bank ratings than Fitch decreases by 26% (18%), if Moody's sovereign rating is inferior than Fitch. These probabilities do not change significantly when the ceiling effects are considered (Eq. 6.3) and show that the probabilities of Moody's superior bank ratings are more sensitive to Moody's inferior sovereign ratings than to Moody's superior sovereign ratings. Regarding the sovereign ceiling, the probability of Moody's assigning one-notch superior bank ratings than Fitch decreases (increases) by 37% (32%) when Fitch (Moody's) ceiling effect occurs. These probabilities suggest that when bank splits occur between these GRAs, Moody's bank rating decisions are highly influenced by Fitch sovereign ceiling.

Table A 6.3 in the Appendix presents the results for superior bank ratings by Moody's than Fitch, and the interaction terms are included. The coefficients of *SSInf*CeF* and *SSup*CeF* are statistically significant. If Fitch bank ratings are below the sovereign rating (*CeF=0*) and Moody's assigns lower sovereign ratings, the probability of one-notch (two-or-more-notches) Moody's superior bank ratings decreases by 33% (26%). In contrast, if Fitch ceiling applies, Moody's bank ratings are less sensitive to their inferior sovereign ratings.

6.6.2 Lower bank ratings from GRA1

Tables 6.8 to 6.10 present the results of Eq. (6.2) and (6.4) for each pair of GRAs. as follows. The coefficients of the split sovereign ratings dummy variables (*SSInf* and *SSup*) are statistically significant across all pairs of GRAs, even when the ceiling effect dummy variables are not considered (Eq. 6.2). However, the Pseudo-R^2 of the models improves significantly when the ceiling effect dummy variables are included (Eq. 6.4). When split bank ratings occur, the probability of two-or-more notches inferior bank ratings by GRA1 is more sensitive to split sovereign ratings and the ceiling effect than the probability of two-or-more notches superior bank ratings by GRA1.

Table 6.8 presents the results for S&P inferior bank ratings than Moody's. The coefficients of split sovereign ratings are significant at the 1% level, even without including the ceiling effect dummy variables *CeSP* and *CeM* (Eq. 6.2). If both split sovereign and the ceiling effect dummy variables are included, the sensitivity of the probabilities of S&P assigning lower bank ratings than Moody's increases greatly. Eq. (6.4) shows that the likelihood of one-notch (two-or-more-notches) inferior S&P bank ratings increases by 11% (13%) if S&P assigns inferior sovereign ratings than Moody's (*SInf*). These results suggest that sovereign opacity is a relevant driver of split bank ratings, although S&P bank ratings are more driven by its own sovereign ratings when disagreeing with Moody's.

Table A 6.4 in the Appendix reports the results for S&P inferior bank ratings than Moody's, including the interaction terms. *SSInf*CeM* is highly significant and has the expected positive sign. The MEs show that when Moody's sovereign ceiling occurs, the probability of one-notch (two-or-more-notches) inferior S&P bank ratings decreases (increases) 13% (35%) when S&P assigns lower sovereign ratings. The difference on the direction and the magnitude of the MEs between one-notch or two-or-more-notches suggests that Moody's ceiling effect triggers in S&P a strong conservative response on bank ratings, if S&P has also lower sovereign ratings than Moody's.

The results of the estimations for S&P inferior bank ratings than Fitch are shown in Table 6.9. The coefficients of the split sovereign dummy variables (*SSInf* and *SSup*) are significant in Eq. (6.2) and (6.4) and have the expected positive and negative signs, respectively. Contrary to the other two pairs of GRAs, in both Eq. (6.2) and (6.4) the probabilities of split bank ratings between S&P and Fitch, with S&P inferior ratings, are more sensitive to inferior S&P sovereign ratings (*SSInf*) than to superior S&P sovereign ratings (*SSup*). Both ceiling dummy variables (*CeSP* and *CeF*) are statistically significant in Eq. (6.4), although Fitch sovereign ceiling has stronger effects.

Table A 6.5 of the Appendix presents the results for S&P inferior bank ratings than Fitch and the interaction terms are included. The coefficients of the interaction terms have high statistical significance. Bank splits have different sensitivities to split sovereign ratings when Fitch ceiling effect occurs. The probability of S&P one-notch (two-or-more-notches) lower bank ratings than Fitch, when S&P assigns lower sovereign ratings, decreases (increases) by 16% (52%), if Fitch sovereign ceiling occurs (*SSInf**CeF*). These results suggest that S&P incorporates the sovereign ceiling of the competitor GRA and its own conservative sovereign rating behaviour when assigning lower bank ratings.

Table 6.10 shows the results considering Moody's inferior bank ratings than Fitch. Adding Moody's and Fitch ceiling effect (Eq. 6.4) increases more than double the Pseudo-R^2. The split sovereign ratings dummy variables (*SSInf* and *SSup*) and the ceiling effect dummy variables (*CeM* and *CeF*) are significant and have the expected sign. The MEs show that the probability of Moody's assigning inferior bank ratings than Fitch is more sensitive to superior Moody's sovereign ratings (*SSup*) and Moody's ceiling effect (*CeM*). Moreover, when Moody's ceiling effect occurs (*CeM*), the likelihood of Moody's one-notch (two-or-more-notches) inferior ratings than Fitch decreases by 44% (36%).

Table A 6.6 of the Appendix presents the results for Moody's inferior bank ratings than Fitch, adding the interaction terms. The MEs of the interaction terms show that the probabilities of bank splits of two-or-more-notches inferior Moody's rating are more sensitive to split sovereign ratings when Fitch sovereign ceiling occurs than one-notch bank splits. These results highlight that Fitch sovereign ceiling strengthens the effect of Moody's sovereign ratings on Moody's bank rating decisions.

In summary, the results support Hypothesis I by showing that split bank ratings are highly responsive to split sovereign ratings and to the sovereign ceiling. Hypothesis II also holds, because GRAs are more likely to be conservative when assigning bank ratings, if they assign a lower sovereign rating than the competitor GRA, while higher sovereign ratings have the opposite effect by increasing the probability of higher bank ratings when split bank ratings occur. Banks with Fitch inferior bank ratings than S&P, are the most sensitive to inferior Fitch sovereign ratings compared to the same scenario for the other pairs of GRAs. The impact of split sovereign ratings on bank rating disagreements is in line with the literature findings on the rating channel for the transmission of sovereign risk to the banking industry (see Shen et al., 2012; Williams et al., 2013). It also provides evidence on the strong sovereign opacity in emerging economies, in line with Vu et al. (2017), and its negative effects on the perception of the GRAs' on the banks' uncertainty.

The results also show that split bank ratings are influenced by sovereign ratings through the ceiling effect. The results relate to the strong effect of the sovereign ceiling on bank ratings found by Williams et al. (2013), Huang and Shen (2015), Adelino and Ferreira (2016) and Drago and Gallo (2017). Additionally, the probabilities of superior bank ratings by any of the GRAs show higher sensitivity to the competitor's ceiling effect than to their own ceiling effect (Tables 6.5 to 6.7). These findings suggest that sovereign ratings assigned by the competitor GRA play a significant role in the GRAs' decision of assigning lower or higher bank ratings when split ratings occur. These findings show the strong effect of competition between GRAs in bank ratings and contribute to the literature on competition and herding behaviour in GRAs (see Section 3.2.2 and 3.2.3).

The examination of the interaction terms shows that split sovereign ratings have a significant effect on split bank ratings when the ceiling effect occurs, supporting Hypothesis III. However, the sensitivity of the probability of inferior or superior bank ratings to split sovereign ratings for GRA1 is stronger when the ceiling effect of GRA2 occurs. Moreover, these sensitivities are greater in bank rating differentials of two-or-more notches than in one-notch, and are stronger for the inferior versus superior split bank rating cases (Tables A 6.4 to A 6.6). Huang and Shen (2015) show that bank ratings which are equal or above the sovereign rating are more sensitive to sovereign rating changes, and bank ratings change more often when the ceiling effect occurs. Thus, a GRA that tends to assign more conservative ratings, might incorporate the sovereign ceiling of the competitor GRA as a signal of information asymmetries, and hence, tends to assign even more conservative bank ratings than the competitor. This might be because any bank rating changes in the next periods due to changes in sovereign ratings, could harm their reputation. These findings highlight the important role of reputation and the significant effect of competition between GRAs (see Sections 3.2.2 and 3.2.3) in explaining rating disagreements. The results also contribute to the literature discussing the effect of the sovereign ceiling in emerging banks (see Williams et al., 2013; Huang and Shen, 2015), showing that the sensitivities of bank ratings, when rating disagreements occur, are strongly linked to the ceiling effect.

6.6.3 Robustness tests

6.6.3.1 The case of split bank ratings across the three GRAs

As a robustness test, the effect of split sovereign ratings on split bank ratings is tested by analysing split bank and sovereign ratings across all three GRAs. Previous research has found that a third rating has additional information value when the issuer has prior ratings by the other two GRAs (Baker and Mansi, 2002; Bongaerts et al., 2012). Moreover, the literature has shown that a third rating influences the quality of the ratings by the other two GRAs (Becker and Milbourn, 2011; Bowe and Larik, 2014). The current sample has 66 banks rated by all three GRAs (1,388 observations). The proportion of bank rating observations where one of the GRAs assigns lower ratings compared to the other two GRAs for S&P, Moody's or Fitch is: 35%, 10% and 4%, respectively, while the proportion of sovereign rating observations is 20%, 3% and 17%, respectively. To incorporate the three-split ratings in the robustness test, the Chapter follows a similar approach as Vu et al. (2015) that acknowledges that higher and lower ratings should be separated when split ratings occur. A probit model approach is employed. The model specification for superior bank ratings is as follows:

$$BankSSup^{*}_{i,z,j,t} = \beta_1 SovInfSP_{j,t} + \beta_2 SovInfMoodys_{j,t} + \beta_3 SovInfFitch_{j,t} + SovRat_{j,t} + \delta YD + \varepsilon_{ijt} \quad (6.5)$$

The model specification for inferior bank ratings is as follows:

$$BankSInf^{*}_{i,z,j,t} = \beta_1 SovSSupSP_{j,t} + \beta_2 SovSSupMoodys_{j,t} + \beta_3 SovSSupFitch_{j,t} + SovRat_{j,t} + \delta YD + \varepsilon_{ijt} \quad (6.6)$$

Where:

$$BankSSup_{i,z,j,t} = \begin{cases} 1 \quad if\ BankSSup^{*}_{i,zj,t} > 0 \\ 0\ if\ BankSSup^{*}_{i,z,j,t} \leq 0 \end{cases}$$

$$BankSInf_{i,a,j,t} = \begin{cases} 1 \quad if\ BankSInf^{*}_{i,z,j,t} > 0 \\ 0\ if\ BankSInf^{*}_{i,z,j,t} \leq 0 \end{cases}$$

The subscripts i, j, t denote bank, country and time (quarters), respectively. The subscript *z* denotes the GRA: S&P, Moody's or Fitch. $BankSSup$ takes a value of one if GRA *z* assigns a bank rating superior to both of the remaining GRAs or the bank rating assigned by GRA *z* is superior to one of them and equal to the other, zero otherwise. $BankSInf$ takes the value of one if GRA *z* assigns a bank rating inferior to both of the remaining GRAs or the bank rating is inferior to one of them and equal to the other, zero otherwise. $SovSSup$ takes the value of one if GRA *z* assigns a sovereign rating superior than both of the remaining GRAs or the sovereign rating is superior to one of them and equal to the other, zero otherwise. $SovSInf$ takes the value of one if GRA *z* assigns a sovereign rating inferior than both of the remaining GRAs or the sovereign rating is inferior to one of them and equal to the other, zero otherwise. $SovSSup$ and $SovSInf$ are estimated for each GRA. $SovRat$ is the average sovereign ratings of all three GRAs based on the 18-point numerical rating scale, in quarter *t* and it is included to control for differences in the economic situation of the countries of the sample. Eqs. (6.5) to (6.6) incorporate a set of year (YD) dummy variables and Huber–White robust standard errors applied (for details see Section 4.5.1).

Table 6.11 presents the results of the estimations of Eqs. (6.5) and (6.6). Overall, sovereign rating disagreements have a significant influence on bank split ratings for all three GRAs. However, the sensitivity of the probabilities of bank split ratings to sovereign split ratings differs between GRAs. The probabilities of S&P and Fitch inferior bank ratings are highly sensitive to each sovereign rating behaviour, while Moody's inferior bank ratings are more influenced by S&P and by Fitch sovereign rating behaviour than by their own rating decisions. These findings are consistent with the results observed in Tables 6.5 to 6.10. Moreover, a novel result is that Fitch is the GRA that has less influence on the bank ratings of the other two GRAs through their sovereign ratings, when the sovereigns and the banks are rated by all three GRAs.

6.6.3.2 An alternative approach to examine split bank ratings

To examine bank rating differences between two GRAs, the common approach is a binary or an ordered probit model. An alternative approach is considering the relative bank split to acknowledge the rating categories. For instance, BankA rated AAA (i.e. 18 numerical rating) by S&P and Aa2 (16 numerical rating) by Moody's, represents a split of two-notches. Likewise, BankB rated B+ (5 numerical rating) by S&P and B3 (3 numerical rating) by Moody's also represents a split of two-notches. However, BankA has an average rating of '17' (AAA=18 and Aa2=16), while BankB has an average rating of '4' (B+=5, B3=3). The split notch-difference between GRAs divided by the average of those ratings (multiplied by 100) can be used to capture the rating categories. In this Chapter, it is referred to as the "relative bank split". For the previous example, the relative bank split for BankA is 10% and for BankB is 50%, showing that the split of two-notches between S&P and Moody's for BankB reflects higher bank risk relative to BankA. The same would apply to sovereign ratings. Therefore, as robustness test this Chapter investigates whether the "relative sovereign split" and the ceiling effect have a significant impact on the "relative bank split", employing an Ordinary Least Squares (OLS) with a fixed-effects approach. Fixed-effect regressions allow controlling for time-invariant heterogeneity among the individuals of the sample (Bessler et al., 2015). As in Eqs. (6.1) to (6.4), the cases where GRA1 assigns higher bank ratings are separated from the cases where GRA1 assigns lower bank ratings (see Section 6.5.1). The model specification for split bank ratings where GRA1 assigns higher bank ratings is as follows:

$$BankRSSup_{i,j,t} = \alpha + \beta_1 SovRS_{j,t} + \beta_2 CeilingGRA1_{i,j,t} + \beta_3 CeilingGRA2_{i,j,t} + \delta YD + \phi CD + \varepsilon_{i,j,t} \quad (6.7)$$

Likewise, the model specification for split bank ratings where GRA1 assigns lower bank ratings is as follows:

$$BankRSInf_{i,j,t} = \alpha + \beta_1 SovRS_{j,t} + \beta_2 CeilingGRA1_{i,j,t} + \beta_3 CeilingGRA2_{i,j,t} + \delta YD + \phi CD + \varepsilon_{i,j,t} \quad (6.8)$$

The subscripts i, j, t denote bank, country and time (quarters), respectively. The variable $BankRSSup$ ($BankRSinf$) is the ratio of the difference between the bank ratings assigned by GRA1 and GRA2 to the average bank rating assigned by GRA1 and GRA2, multiplied by 100, for cases where GRA1 assigns higher (lower) ratings than GRA2. $SovRS$ is the "relative sovereign split". Namely, the ratio of the difference between the sovereign ratings assigned by GRA1 and GRA2 to the average sovereign ratings assigned by GRA1 and by GRA2, multiplied by 100.[148] *CeilingGRA1* and *CeilingGRA2* refer to the ceiling effect of each GRA and have the

[148] Bank ratings and sovereign ratings are based on 18-point numerical scale (see Section 5.4.1).

same definition as in Section 6.5.1.2. Two types of models are estimated for Eqs. (6.7) and (6.8). The Model I includes only split sovereign ratings and Model II includes the effect of the split sovereign ratings and the ceiling effect. The models include a set of year (*YD*) and country dummy variables (*CD*) and the robust standard errors are clustered at bank level, to account for any within-bank correlation that has not been captured by the fixed effects (see Section 4.5.1).

Tables 6.12 to 6.14 present the results of the estimations of Eqs. (6.7) and (6.8). Overall, the results show consistently across all pairs of GRAs that split sovereign ratings and the ceiling effects have a significant effect in explaining the relative bank split, confirming the rating channel in banks from emerging economies. Higher R^2 values are observed when the ceiling effect dummy variables are incorporated into the equation compared to the models with only the sovereign rating. Together, split sovereign ratings and the ceiling effect dummy variables explain about 30% of the total variance of the "relative bank split".[149] Furthermore, the R^2 values of Eq. (6.8) Model II suggests that that the relative sovereign split and the ceiling effect have higher explanatory power when evaluating the inferior bank ratings by GRA1 than when examining superior bank ratings by GRA1.

The results of Eq. (6.7) show for all pairs of GRAs (Tables 6.12 to 6.14) that higher relative sovereign split (*SovRS*) is associated with higher relative bank split. Model II shows that the strongest effect of the relative sovereign split (*SovRS*) on the relative bank split is observed for banks jointly rated by S&P and Fitch. Namely, an increase of 1 percentage point in the relative sovereign split between S&P and Fitch increases on average by 52 percentage points the relative bank split (for S&P and Moody's by 42 percentage points and for Moody's and Fitch by 26 percentage points) keeping the other variables constant. For all three GRAs, the ceiling effect of GRA1 (GRA2) increases (decreases) the relative split ratings. The coefficient of the relative sovereign split is larger than the coefficients of the ceiling effect dummy variables, suggesting that the relative sovereign split has a stronger impact on the relative bank split than the ceiling effect.

The results for Eq. (6.8), which shows the cases where GRA1 assigns inferior bank ratings, shows that all coefficients are statistically significant, although the coefficient of the relative sovereign split has a larger magnitude than those from the ceiling effect dummy variables (as

[149] Split sovereign ratings and the ceiling effect explain on average 15.8% of the total variance of the relative bank split when GRA1 assigns a superior bank rating (13.4% for S&P and Moody's, 18.4% for S&P and Fitch and 15.5% for Moody's and Fitch), and when GRA1 assigns an inferior bank rating, they explain on average of 27.1% of the total variance of the relative bank split (21.6% for S&P and Moody's, 34.6% for S&P and Fitch and 25.2% for Moody's and Fitch).

evidenced in Eq. 6.7). Table 6.12, Eq. (6.8) Model II shows that S&P and Fitch have the highest coefficient of *SovSR* compared to S&P and Moody's and Moody's and Fitch, whereby 1 percentage point increase in *SovSR* decreases by 58 percentage points the relative bank split when S&P assigns lower bank ratings. When S&P (Fitch) ceiling effect applies (*CeSP* or *CeF*), the average relative bank split between S&P and Fitch decreases (increases) 9.4 (7.41) percentage points. Among the pairs of GRAs, the highest coefficient of the ceiling effect dummy variables corresponds to Moody's ceiling effect (*CeM*), when banks are jointly rated by Moody's and Fitch. Moody's ceiling effect decreases the average relative bank split between Moody's and Fitch by 15.9 percentage points keeping constant the other variables.

6.7 Conclusions

There is a well-established connection between the banking industry and the government, especially during financial distress periods (Alsakka et al., 2014; Correa and Sapriza, 2014; Adelino and Ferreira, 2016). Sovereign risk can be transmitted to the banking industry through the effects of sovereign rating actions on bank rating actions, a link that is strengthened by the ceiling effect, especially in emerging economies (Williams et al., 2013; Huang and Shen, 2015). Despite the significant evidence on the link between sovereigns and banks, studies of credit rating disagreements between GRAs have neglected the connection. Thus, this Chapter makes a unique contribution to the literature of split ratings by investigating the effect of sovereign risk on bank rating disagreements between GRAs in emerging economies. To address the sovereign risk, the Chapter uses as a proxy the split sovereign ratings, which incorporate the political risk and the level of information disclosure (Vu et al., 2017). The Chapter also analyses if there is asymmetric behaviour in split sovereign ratings, whereby one GRA tends to assign a lower rating, and if that asymmetries have an impact on the bank rating behaviour. Furthermore, as the literature shows that the effect of sovereign rating changes on bank rating changes is stronger when the ceiling effect takes place (Huang and Shen, 2015), the third objective of this Chapter is to examine if the ceiling effect also influences the impact of sovereign ratings on bank rating disagreements.

The empirical evidence is based on a sample of 1,898 observations (92 banks) from 9 emerging economies rated by S&P and Moody's; 1,767 observations (95 banks) across 10 emerging economies rated by S&P and Fitch; and 2,423 observations (111 banks) across 10 countries rated by Moody's and Fitch, during October 2008 to December 2015. The descriptive analysis shows that S&P tends to assign lower bank ratings than Moody's (Fitch) in 80.7% (78.1%) of the total bank splits observations. S&P also assigns sovereign ratings in a more conservative manner than Moody's (Fitch), assigning lower sovereign ratings in 90.2% (62.6%) of the total sovereign splits observations. For banks jointly rated by Moody's and Fitch, Fitch assigns lower bank (sovereign) ratings in 58.8% (88.9%) of the total split observations. The ceiling effect is common in the sample, as on average, 50% of the total observations in each pair of GRAs have bank ratings equal to or higher than the sovereign rating. Because of the discrete and ordinal nature of split bank ratings data, an ordered probit model approach is employed and the MEs are estimated.

The results strongly suggest that sovereign opacity, reflected by split sovereign ratings, should be considered when examining bank rating disagreements between GRAs. The significant effect of split sovereign ratings on bank ratings is corroborated when using the relative bank split as the dependent variable, namely the split notch-difference between GRAs divided by the average of those ratings. Moreover, when the ceiling effect dummy variables are included in addition to split sovereign ratings, both variables are significant and the Pseudo-R^2 values of the ordered probit models improve, implying that both split sovereign ratings and the ceiling effect should be part of the systematic component of split bank ratings. Further, S&P inferior sovereign rating assignments compared to Fitch have a strong effect on the likelihood of S&P assigning inferior bank ratings than Fitch. In contrast, for banks jointly rated by S&P and Moody's (Moody's and Fitch), the probability of S&P (Moody's) assigning inferior bank ratings than Moody's (Fitch) decreases significantly when S&P (Moody's) assigns superior sovereign ratings. Moreover, the results show that the effect of sovereign opacity has more economic significance for split bank ratings between S&P and Fitch, as the probabilities of assigning inferior bank ratings when superior (or inferior) sovereign ratings are assigned, are greater for S&P and Fitch than for the other two pairs of GRAs,

For S&P and Moody's (Moody's and Fitch), the economic impact of S&P (Moody's) assigning inferior sovereign ratings on S&P (Moody's) inferior bank ratings than Moody's (Fitch), is similar for one-notch or two-or-more-notches bank ratings. In contrast, for S&P and Fitch, the economic effect of S&P inferior sovereign rating assignments on S&P assigning one-notch inferior bank ratings is greater than for two-or-more-notches inferior bank ratings. The results for S&P and Fitch are driven by the higher number of split bank ratings of one-notch compared to splits of two-or-more-notches. Furthermore, the analysis of the case of split bank ratings by the three GRAs shows that the tendency of S&P to assign inferior sovereign ratings, versus at least one of the other two GRAs, has the strongest effect on S&P, Moody's and Fitch superior bank ratings. On the other hand, inferior sovereign ratings assigned by Fitch have the weakest impact on superior bank ratings by any or both S&P and Moody's.

The probability of assigning superior or inferior bank ratings by any of the GRAs is more significant when the ceiling effect from the competitor GRA applies, except for S&P and Moody's. In the latter case, S&P ceiling effect has similar economic significance than Moody's ceiling effect on the likelihood of S&P inferior bank rating assignments. Further, to examine if split bank ratings are more sensitive to split sovereign ratings if the ceiling effect occurs, an additional model is estimated for each pair of GRAs, including the interaction between the split sovereign ratings dummy variables and the ceiling effect dummy variables. The results show that S&P superior bank rating assignments than Moody's (or Fitch) are more sensitive to split sovereign ratings, when S&P ceiling effect prevails. For banks jointly rated by Moody's and Fitch, the probability of Moody's superior bank ratings reacts stronger to Moody's lower sovereign rating assignments, if Fitch ceiling effect occurs than when there is no ceiling effect.

Split sovereign ratings have a stronger impact on the probability of one-notch superior bank ratings when the ceiling effect occurs than in two-or-more notches superior bank ratings. This is most likely because the number of observations with S&P or Moody's superior bank ratings of more than one-notch are extremely low (see Table 6.2). In contrast, for inferior bank ratings the ceiling effect is stronger when the rating difference is of two-or-more-notches. Namely, S&P is more likely to assign two-or-more-notches inferior bank ratings than Moody's (or Fitch) when S&P assigns inferior sovereign ratings, if Moody's (or Fitch) ceiling effect prevails. In comparison, if the ceiling effect of Moody's (Fitch) does not occur, there is higher probability of S&P assigning one-notch inferior bank rating than Moody's (or Fitch), if S&P assigns inferior sovereign ratings than Moody's (or Fitch). The same results are achieved when analysing Moody's and Fitch split ratings. Namely, when Moody's assigns inferior sovereign ratings than Fitch, the economic effect of Fitch ceiling is more significant in two-or-more-notches than in one-notch inferior bank ratings assigned by Moody's. These results suggest that when a given GRA perceives higher sovereign opacity, lower bank rating assignments depend on whether the bank ratings of the competitor GRA are below, at or above the sovereign rating.

The findings of the Chapter have important insights. First, the GRAs' perception of government transparency has an asymmetric effect on split bank ratings, because one of the GRAs tends to assign lower bank and sovereign ratings. Second, using split sovereign ratings as drivers of split bank ratings provides an alternative framework to investigate the transmission of sovereign risk to bank risk through the rating channel. Thus, split sovereign ratings can shed light on the contagion effect in the banking industry when sovereign distress occurs. Thirdly, because the ceiling effect has a significant influence on bank rating disagreements, and banks with ratings equal or higher than the sovereign ratings are more sensitive to sovereign rating changes, the findings suggest that in countries with higher government opacity, which are more propense to sovereign rating changes, the banking industry would show higher proportion of rating disagreements.

The findings of the Chapter support the need for legislation that improves the quality of information and anti-corruption laws to improve government transparency and information quality. The perception of less sovereign uncertainty should decrease the sovereign rating disagreements among the GRAs thereby, discouraging split bank ratings. Moreover, policies that promote less connection between the sovereign and the bank ratings should reduce the strong ceiling effect observed in emerging economies, which would favour less split bank ratings.

Because of the significant impact of split sovereign ratings and the ceiling effect on split bank ratings, future research may study if the systematic component of split bank ratings is priced into banks' bond yields or in bank stock returns. Moreover, sovereign opacity in emerging economies is associated with a lack of government transparency. Thus, future research could investigate if the influence of bank-specific factors (idiosyncratic component) on split bank ratings in emerging economies can be distorted by the level of government corruption.

Chapter 6 Tables

Table 6.1 General statistics on credit ratings

Concept	S&P and Moody's	S&P and Fitch	Moody's and Fitch
Countries	9	10	10
Number of banks with split ratings[a]	87	82	107
Number of banks with no split ratings	5	8	4
Number of sovereigns with split ratings	7	10	10
Number of sovereigns with no split ratings[b]	2	0	0
Number of observations	1,898	1,767	2,423
Number of split bank ratings observations	1,418	962	1,679
Number of split sovereign ratings observations	1,169	698	1,634
Split bank ratings (as % of total observations)	74.7%	54.4%	69.3%
Split sovereign ratings (as % of total observations)	61.6%	39.5%	67.4%
Detail of split bank ratings in notches			
1 notch	1,082	741	1,178
2 notches	290	190	425
3 notches	45	29	69
> 3 notches	1	2	7
Detail of split sovereign ratings in notches			
1 notch	955	684	1,414
2 notches	98	14	57
3 notches	42	0	91
> 3 notches	73	0	72

The table reports the descriptive statistics of the data sample for each pair of GRAs during the period October 2008 to December 2015 (2008Q4-2015Q4). S&P, Moody's, and Fitch bank ratings are transformed into numerical ratings based on an 18-point numerical scale. ***a.*** *At least one quarter with split ratings* ***b****. China and Thailand do not have split sovereign ratings between S&P and Moody's during the period of analysis.*

Table 6.2 Split bank and split sovereign ratings considering superior and inferior ratings

	S&P and Moody's		*S&P and Fitch*		*Moody's and Fitch*	
Concept	Superior S&P	Inferior S&P	Superior S&P	Inferior S&P	Superior Moody's	Inferior Moody's
Split bank ratings	273	1,145	211	751	987	692
Split bank ratings *(as % of total splits)*	19.3%	80.7%	21.9%	78.1%	58.8%	41.2%
Split bank ratings in notches (Number of observations)						
1 Notch	203	879	178	563	762	416
2 ≥ Notches	70	266	33	188	225	276
Split sovereign ratings	115	1,054	261	437	1,452	182
Split sovereign ratings *(as % of total splits)*	9.8%	90.2%	37.4%	62.6%	88.9%	11.1%

The table presents the summary of split bank ratings and split sovereign ratings observations for each pair of GRAs during the period October 2008 to December 2015. The cases where GRA1 assigns superior (or higher) bank or sovereign ratings than GRA2, are separated from the cases where GRA1 assigns inferior (or lower) bank or sovereign ratings than GRA2.

Table 6.3 Number of bank ratings lower, equal or higher than the sovereign rating

	S&P and Moody's		*S&P and Fitch*		*Moody's and Fitch*	
Concept	S&P	Moody's	S&P	Fitch	Moody's	Fitch
Bank ratings = Sovereign ratings	760	628	815	560	768	761
Bank ratings > Sovereign ratings	19	121	16	311	195	449
Bank ratings < Sovereign ratings	1,119	1,149	936	896	1,460	1,213
As % of total observations						
Bank ratings = Sovereign ratings	40.0%	33.0%	46.1%	31.7%	31.7%	31.4%
Bank ratings > Sovereign ratings	1.0%	6.0%	0.9%	17.6%	8.0%	18.5%
Bank ratings < Sovereign ratings	59.0%	61.0%	53.0%	50.7%	60.3%	50.1%

The table reports the number and percentages of the bank ratings that are equal, above or below the sovereign ratings for the sample rated by each pair of GRAs during the period October 2008 to December 2015. In this Chapter ceiling effect refers to bank ratings that are equal or above the sovereign ratings.

Table 6.4 Expected signs of the coefficients

Variable	Definition	*Eq. (6.1)*	*Eq. (6.2)*	*Eq. (6.3)*	*Eq. (6.4)*
SSInf	Dummy variable that takes the value of one when GRA1 assigns a lower rating than GRA2	-	+	-	+
SSup	Dummy variable that takes the value of one when GRA1 assigns a higher rating than GRA2	+	-	+	-
CeGRA1	Dummy variable that takes the value of one when the bank rating is equal or higher than the sovereign rating, both assigned by GRA1	N/A	N/A	+	-
CeGRA2	Dummy variable that takes the value of one when the bank rating is equal or higher than the sovereign rating, both assigned by GRA2	N/A	N/A	-	+

The table presents a description of the variables used in the estimations of Eqs. (6.1) to (6.4) and the expected sign of the variables in each of the equations. 'N/A' is not applicable due to the model specification.

Table 6.5 Split bank ratings' systematic components –Superior S&P ratings than Moody's

	Dependent Variable: *BankSSup*			
	Eq. (6.1)	Eq. (6.3)	ME (%)	
Variable			1	2
SSInf	0.09	-0.66***	-0.17	-0.05
	(0.79)	(-4.64)		
SSup	0.06	-0.20		
	(0.28)	(-0.90)		
CeSP		0.89***	0.22	0.09
		(7.57)		
CeM		-2.46***	-0.38	-0.10
		(-9.21)		
Observations	750	750		
Pseudo R-Squared	9.6%	19.1%		
Country FE	Yes	Yes		
Year FE	Yes	Yes		

The table reports the results of ordered probit estimations (Eqs. (6.1) and (6.3)) using quarterly data from S&P and Moody's for the period October 2008 to December 2015. The dependent variable ***BankSSup*** *denotes split bank ratings (of one-notch or two-or-more-notches), where S&P assigns superior bank ratings than Moody's. For details on the explanatory variables see Section 6.5.1. Full sets of country and year dummies are included in Eqs. (6.1) and (6.3). Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table 6.6 Split bank ratings' systematic components – Superior S&P ratings than Fitch

	Dependent Variable: *BankSSup*			
	Eq. (6.1)	Eq. (6.3)	ME (%)	
Variable			1	2
SSInf	0.16	-0.63***	-0.09	-0.00
	(1.05)	(-3.49)		
SSup	0.10	1.54***	0.21	0.01
	(0.62)	(5.40)		
CeSP		1.20***	0.16	0.01
		(8.35)		
CeF		-2.79***	-0.38	-0.02
		(-12.56)		
Observations	1,013	1,013		
Pseudo R-Squared	11.0%	30.1%		
Country FE	Yes	Yes		
Year FE	Yes	Yes		

The table reports the results of ordered probit estimations (Eqs. (6.1) and (6.3)) using quarterly data from S&P and Fitch for the period October 2008 to December 2015. The dependent variable ***BankSSup*** *denotes split bank ratings (of one-notch or two-or-more-notches), where S&P assigns superior bank ratings than Fitch. For details on the explanatory variables see Section 6.5.1. Full sets of country and year dummies are included in Eqs. (6.1) and (6.3). Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table 6.7 Split bank ratings' systematic components – Superior Moody's ratings than Fitch

	Dependent Variable: *BankSSup*					
	Eq. (6.1)	ME (%)		Eq. (6.3)	ME (%)	
Variable		1	2		1	2
SSInf	-1.12***	-0.26	-0.18	-1.01***	-0.25	-0.14
	(-3.26)			(-2.78)		
SSup	0.11			0.48***	0.12	0.06
	(1.27)			(4.98)		
CeM				1.28***	0.32	0.18
				(13.02)		
CeF				-1.47***	-0.37	-0.21
				(-14.40)		
Observations	1,728			1,728		
Pseudo R-Squared	13.3%			19.9%		
Country FE	Yes			Yes		
Year FE	Yes			Yes		

The table reports the results of ordered probit estimations (Eqs. (6.1) and (6.3)) using quarterly data from Moody's and Fitch for the period October 2008 to December 2015. The dependent variable ***BankSSup*** *denotes split bank ratings (of one-notch or two-or-more-notches), where Moody's assigns superior bank ratings than Fitch. For details on the explanatory variables see Section 6.5.1. Full sets of country and year dummies are included in Eqs. (6.1) and (6.3). Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table 6.8 Split bank ratings' systematic components – Inferior S&P ratings than Moody's

	Dependent Variable: *BankSInf*					
	Eq. (6.2)	ME (%)		Eq. (6.4)	ME (%)	
Variable		1	2		1	2
SSInf	0.56***	0.07	0.12	0.77***	0.11	0.13
	(5.41)			(6.80)		
SSup	-1.04***	-0.12	-0.22	-1.63***	-0.23	-0.27
	(-4.96)			(-7.32)		
CeSP				-1.72***	-0.24	-0.28
				(-19.08)		
CeM				1.65***	0.23	0.27
				(19.21)		
Observations	1,625			1,625		
Pseudo R-Squared	10.2%			17.6%		
Country FE	Yes			Yes		
Year FE	Yes			Yes		

The table reports the results of ordered probit estimations (Eqs. (6.2) and (6.4)) using quarterly data from S&P and Moody's for the period October 2008 to December 2015. The dependent variable ***BankSInf*** *denotes split bank ratings (of one-notch or two-or-more-notches), where S&P assigns inferior bank ratings than Moody's. For details on the explanatory variables see Section 6.5.1. Full sets of country and year dummies are included in Eqs. (6.2) and (6.4). Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table 6.9 Split bank ratings' systematic components – Inferior S&P ratings than Fitch

	Dependent Variable: *BankSInf*					
	Eq. (6.2)	ME (%)		Eq. (6.4)	ME (%)	
		1	2		1	2
SSInf	1.11***	0.29	0.15	1.47***	0.44	0.14
	(10.60)			(13.80)		
SSup	-0.41***	-0.11	-0.05	-0.85***	-0.26	-0.08
	(-3.55)			(-6.12)		
CeSP				-1.35***	-0.41	-0.13
				(-14.11)		
CeF				1.89***	0.57	0.18
				(16.47)		
Observations	1,561			1,561		
Pseudo R-Squared	16.4%			25.8%		
Country FE	Yes			Yes		
Year FE	Yes			Yes		

The table reports the results of ordered probit estimations (Eqs. (6.2) and (6.4)) using quarterly data from S&P and Fitch for the period October 2008 to December 2015. The dependent variable ***BankSInf*** *denotes split bank ratings (of one-notch or two-or-more-notches), where S&P assigns inferior bank ratings than Fitch. For details on the explanatory variables see Section 6.5.1. Full sets of country and year dummies are included in Eqs. (6.2) and (6.4). Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table 6.10 Split bank ratings' systematic components – Inferior Moody's ratings than Fitch

	Dependent Variable: *BankSInf*					
	Eq. (6.2)	ME (%)		Eq. (6.4)	ME (%)	
		1	2		1	2
SSInf	0.29**	0.04	0.08	0.31**	0.06	0.07
	(2.28)			(2.20)		
SSup	-0.36***	-0.06	-0.08	-0.80***	-0.16	-0.15
	(-3.84)			(-8.15)		
CeM				-2.02***	0.33	0.31
				(-18.12)		
CeF				1.86***	-0.38	-0.28
				(15.44)		
Observations	1,432			1,432		
Pseudo R-Squared	12.7%			26.8%		
Country FE	Yes			Yes		
Year FE	Yes			Yes		

The table reports the results of ordered probit estimations (Eqs. (6.2) and (6.4)) using quarterly data from Moody's and Fitch for the period October 2008 to December 2015. The dependent variable ***BankSInf*** *denotes split bank ratings (of one-notch or two-or-more-notches), where Moody's assigns inferior bank ratings than Fitch. For details on the explanatory variables see Section 6.5.1. Full sets of country and year dummies are included in Eqs. (6.2) and (6.4). Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table 6.11 Split bank ratings' systematic components – The case of triple bank ratings

Panel A.	*Dependent variable: BankSSup*					
	S&P		*Moody's*		*Fitch*	
Variable	Eq.(6.5)	ME (%)	Eq.(6.5)	ME (%)	Eq.(6.5)	ME (%)
SovInfSP	-0.41***	-0.03	0.17**	0.07	0.33***	0.13
	(-3.13)		(1.99)		(3.66)	
SovInfMoodys	1.70***	0.36	-1.13***	-0.41	-0.28*	-0.11
	(9.39)		(-5.68)		(-1.67)	
SovInfFitch	0.22		0.07		0.29**	0.11
	(1.37)		(0.61)		(2.19)	
SovRat	0.03		0.10***	0.04	-0.25***	-0.10
	(0.78)		(4.02)		(-8.52)	
Observations	1,388		1,388		1,388	
Pseudo R-Squared	24.7%		4.7%		10.0%	
Year FE	Yes		Yes		Yes	

Panel B.	*Dependent variable: BankSInf*					
	S&P		*Moody's*		*Fitch*	
Variable	Eq.(6.6)	ME (%)	Eq.(6.6)	ME (%)	Eq.(6.6)	ME (%)
SovSupSP	-1.06***	-0.40	1.52***	0.47	-0.24	
	(-5.19)		(8.50)		(-1.41)	
SovSupMoodys	0.57***	0.21	-0.28**	-0.05	0.18**	0.06
	(7.03)		(-2.48)		(2.20)	
SovSupFitch	-0.05		0.53***	0.11	-1.23***	-0.34
	(-0.49)		(3.63)		(-8.31)	
SovRat	0.17***	0.06	-0.14***	-0.02	0.09***	0.03
	(6.26)		(-3.19)		(3.68)	
Observations	1,388		1,388		1,388	
Pseudo R-Squared	9.1%		17.3%		9.5%	
Year FE	Yes		Yes		Yes	

The table reports the results of probit estimations (Eqs. (6.5) and (6.6)) using quarterly data from S&P, Moody's and Fitch for the period October 2008 to December 2015. In ***Panel A****, the dependent variable* ***BankSSup*** *takes a value of one if GRA z (z=S&P, Moody's or Fitch) assigns a bank rating superior to both of the remaining GRAs or the bank rating assigned by GRA z is superior to one of them and equal to the other, zero otherwise. In* ***Panel B****, the dependent variable* ***BankSInf*** *takes the value of one if GRA z assigns a bank rating inferior to both of the remaining GRAs or the bank rating is inferior to one of them and equal to the other, zero otherwise. For details on the explanatory variables see Section 6.6.3. Full sets of year dummies are included in Eqs. (6.5) and (6.6). Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. The marginal effects (ME) are reported only for variables with significant (at 5% or better) coefficients. For details on the estimation of the MEs see Section 5.5.1.*

Table 6.12 Split bank ratings' components for S&P and Moody's, using relative split ratings

Panel A.	Dependent variable*: BankRSSup* (Eq. 6.7)	
Variable	(I)	(II)
SovRS	0.35***	0.42***
	(2.88)	(3.15)
CeSP		8.10***
		(3.44)
CeM		-7.08***
		(-2.83)
Constant	9.25***	7.62***
	(3.63)	(2.97)
Observations	750	750
R-Squared	10.5%	13.4%
Panel B.	Dependent variable: *BankRSInf* (Eq. (6.8)	
	(I)	(II)
SovRS	-0.06	-0.25***
	(-0.74)	(-2.85)
CeSP		-6.59***
		(-3.26)
CeM		10.15***
		(6.46)
Constant	13.31***	8.97***
	(8.69)	(5.14)
Observations	1,625	1,625
R-Squared	8.7%	21.6%
Country FE	Yes	Yes
Year FE	Yes	Yes

*The table reports the results of the OLS with fixed-effects model (Eqs. (6.7) and (6.8)) using quarterly rating data from S&P and Moody's for the period October 2008 to December 2015. In **Panel A (Panel B)** the dependent variable **BankRSSup (BankRSInf)** is the ratio of the difference between bank ratings assigned by S&P and Moody's to the average bank rating assigned by S&P and Moody's, multiplied by 100, for cases where S&P assigns superior (inferior) ratings than Moody's. Model (I) includes split sovereign ratings dummy variables (SSInf and SSup). Model (II) includes the split sovereign ratings dummy variables (SSInf and SSup), and S&P and Moody's ceiling effect dummy variables (CeSP and CeM, respectively). The definition of the explanatory variables is detailed in Section 6.6.3.2. Standard errors clustered at the bank level. Full set of country and year dummies are included. Z-statistics are reported beneath each coefficient. *, ** and *** indicate statistical significance at the 10%, 5% and 1%.*

Table 6.13 Split bank ratings' components for S&P and Fitch, using relative split ratings

Panel A.	Dependent variable*: BankRSSup* (Eq. 6.7)	
Variable	(I)	(II)
SovRS	0.46***	0.52***
	(3.52)	(3.94)
CeSP		6.85***
		(3.35)
CeF		-5.88***
		(-3.29)
Constant	5.64***	4.60***
	(4.71)	(3.88)
Observations	1,013	1,013
R-Squared	15.3%	18.4%
Panel B.	Dependent variable: *BankRSInf* (Eq. (6.8)	
Variable	(I)	(II)
SovRS	-0.46***	-0.60***
	(-5.85)	(-7.51)
CeSP		-9.40***
		(-10.55)
CeF		7.41***
		(6.66)
Constant	6.55***	6.33***
	(7.44)	(6.46)
Observations	1,554	1,554
R-Squared	19.3%	34.6%
Country FE	Yes	Yes
Year FE	Yes	Yes

The table reports the results of the OLS with fixed-effects model (Eqs. (6.7) and (6.8)) using quarterly rating data from S&P and Fitch for the period October 2008 to December 2015. In ***Panel A (Panel B)*** *the dependent variable* ***BankRSSup (BankRSInf)*** *is the ratio of the difference between bank ratings assigned by S&P and Fitch to the average bank rating assigned by S&P and Fitch, multiplied by 100, for cases where S&P assigns superior (inferior) ratings than Fitch. Model (I) includes split sovereign ratings dummy variables (SSInf and SSup). Model (II) includes the split sovereign ratings dummy variables (SSInf and SSup), and S&P and Fitch ceiling effect dummy variables (CeSP and CeF, respectively). The definition of the explanatory variables is detailed in Section 6.6.3.2. Standard errors clustered at the bank level. Full set of country and year dummies are included. Z-statistics are reported beneath each coefficient. $*$, $**$ and $***$ indicate statistical significance at the 10%, 5% and 1%.*

Table 6.14 Split bank ratings' components for Moody's and Fitch, using relative split ratings

	Dependent variable*: BankRSSup* (Eq. 6.7)	
Variable	(I)	(II)
SovRS	0.15*	0.26**
	(1.70)	(2.49)
CeM		6.06***
		(2.97)
CeF		-7.07***
		(-4.29)
Constant	11.48***	10.93***
	(6.49)	(4.87)
Observations	1,728	1,728
R-Squared	10.5%	15.5%
Panel B.	Dependent variable: *BankRSInf* (Eq. (6.8)	
Variable	(I)	(II)
SovRS	-0.22***	-0.27**
	(-2.67)	(-2.20)
CeM		-15.90***
		(-6.11)
CeF		7.01**
		(2.39)
Constant	16.47***	14.52***
	(5.82)	(5.15)
Observations	1,432	1,432
R-Squared	8.6%	25.2%
Country FE	Yes	Yes
Year FE	Yes	Yes

*The table reports the results of the OLS with fixed-effects model (Eqs. (6.7) and (6.8)) using quarterly rating data from Moody's and Fitch for the period October 2008 to December 2015. In **Panel A (Panel B)** the dependent variable **BankRSSup (BankRSInf)** is the ratio of the difference between bank ratings assigned by Moody's and Fitch to the average bank rating assigned by Moody's and Fitch, multiplied by 100, for cases where Moody's assigns superior (inferior) ratings than Fitch. Model (I) includes split sovereign ratings dummy variables (SSInf and SSup). Model (II) includes the split sovereign ratings dummy variables (SSInf and SSup), and Moody's and Fitch ceiling effect dummy variables (CeM and CeF, respectively). The definition of the explanatory variables is detailed in Section 6.6.3.2. Standard errors clustered at the bank level. Full set of country and year dummies are included. Z-statistics are reported beneath each coefficient. *, ** and *** indicate statistical significance at the 10%, 5% and 1%.*

Chapter 6 Figures

Figure 6.1 Comparison between banks and sovereign split ratings

Figure A. S&P assigns inferior ratings than Moody's

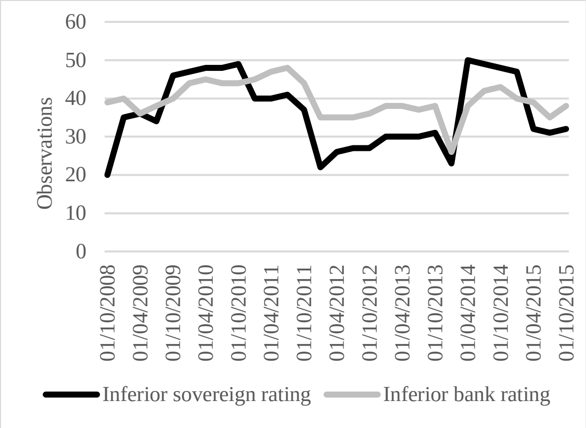


Figure B. S&P assigns superior ratings than Moody's

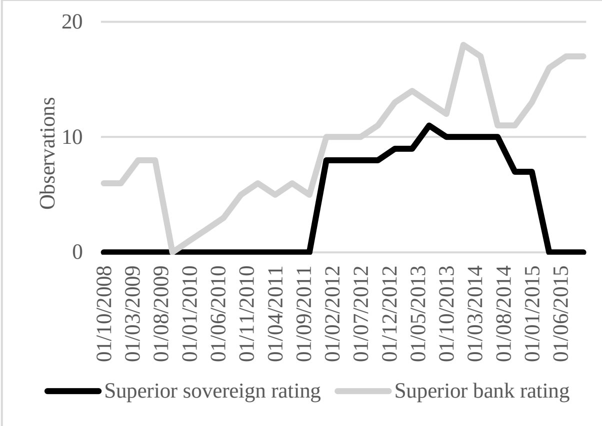


Figure C. S&P assigns inferior ratings than Fitch

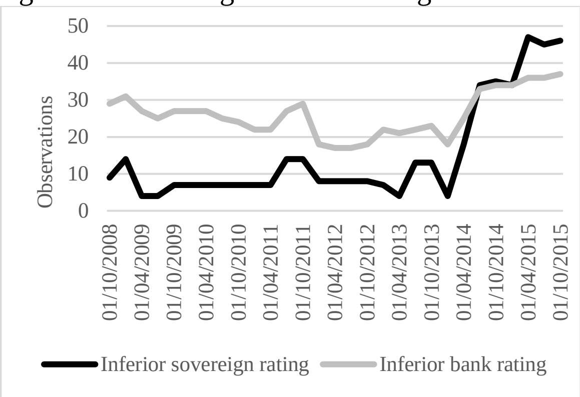


Figure D. S&P assigns superior ratings than Fitch

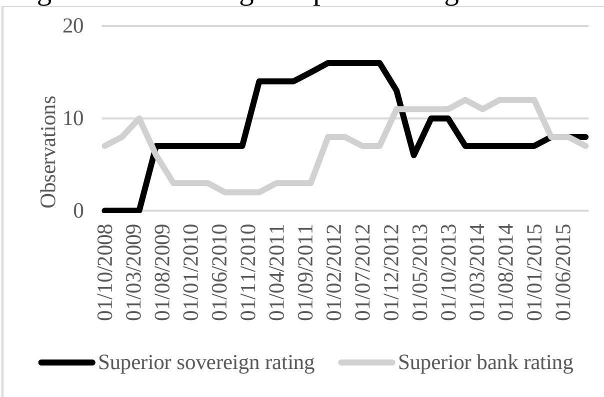


Figure E. Moody's assigns inferior ratings than Fitch

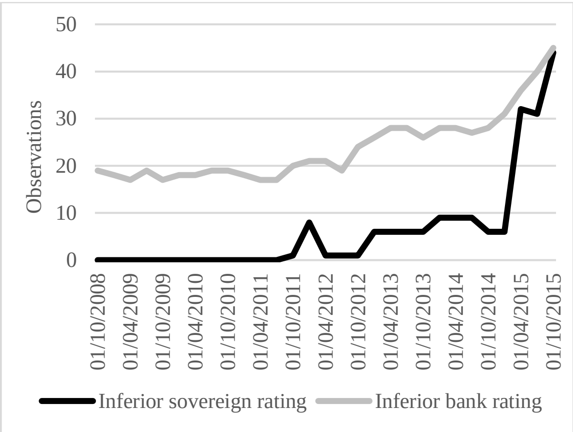
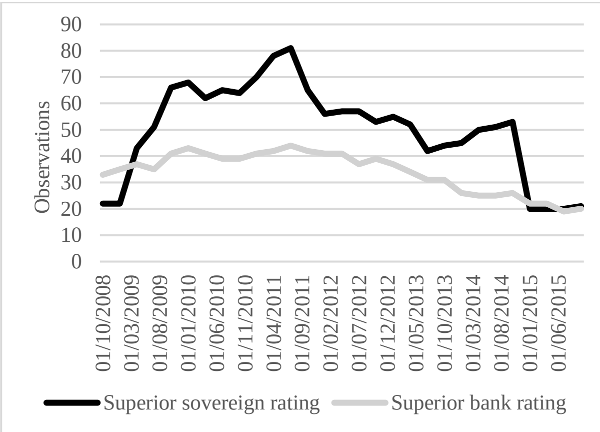


Figure F. Moody's assigns inferior ratings than Fitch



The figure present the evolution of split bank and sovereign ratings, considering inferior and superior sovereign and bank ratings during the period of October 2008 to December 2015. Figure A (Figure B) presents the number of observations when S&P assigns inferior (superior) ratings than Moody's. Figure C (Figure D) presents the number of observations when S&P assigns inferior (superior) ratings than Fitch. Figure E (Figure F) presents the number of observations when Moody's assigns inferior (superior) ratings than Fitch.

Figure 6.2 Sovereign ratings and average bank ratings in each country

Figure A. Brazil sovereign ratings vs. Average bank ratings

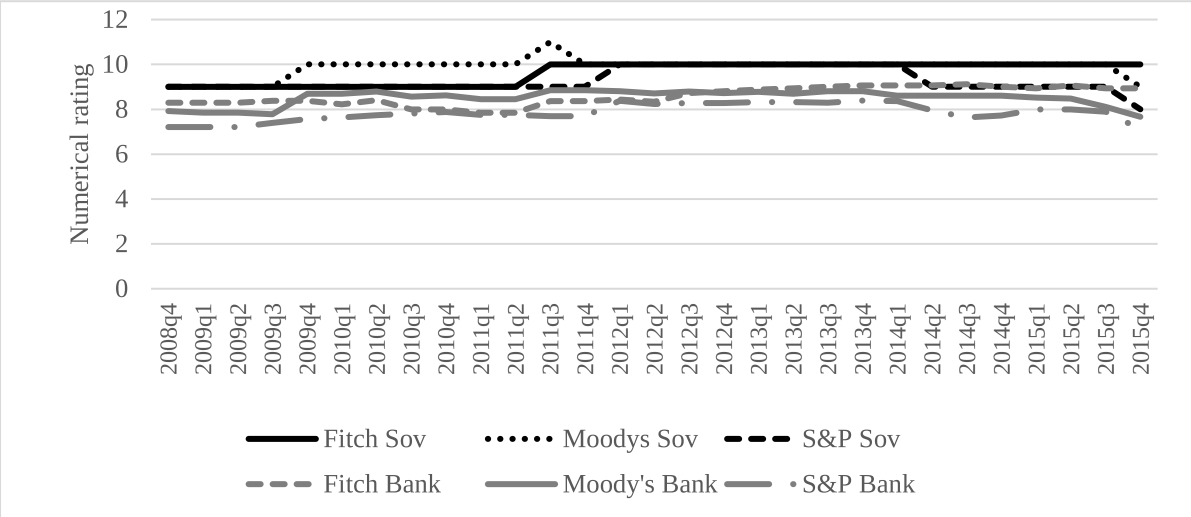


Figure B. Colombia sovereign ratings vs. Average bank ratings

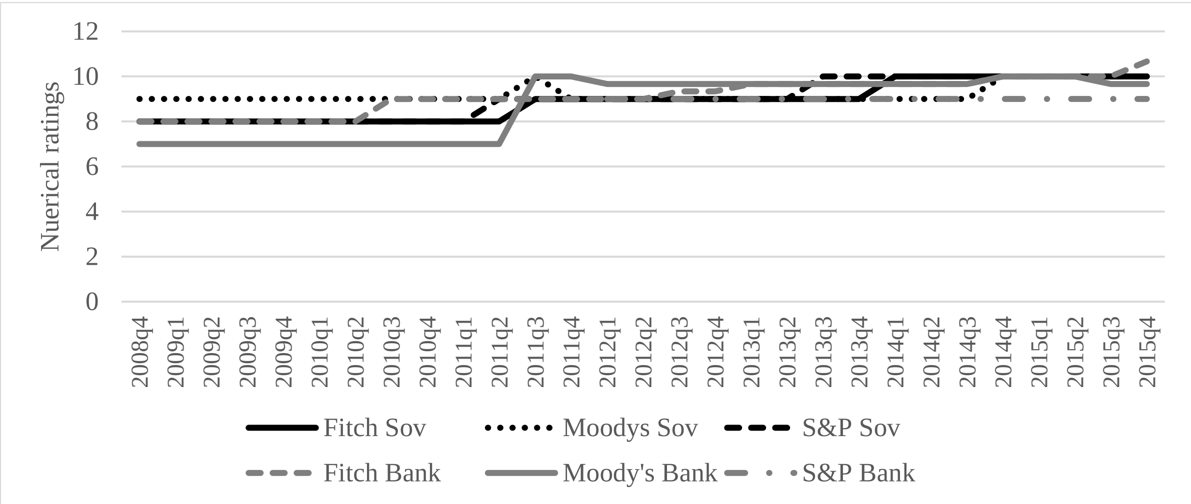
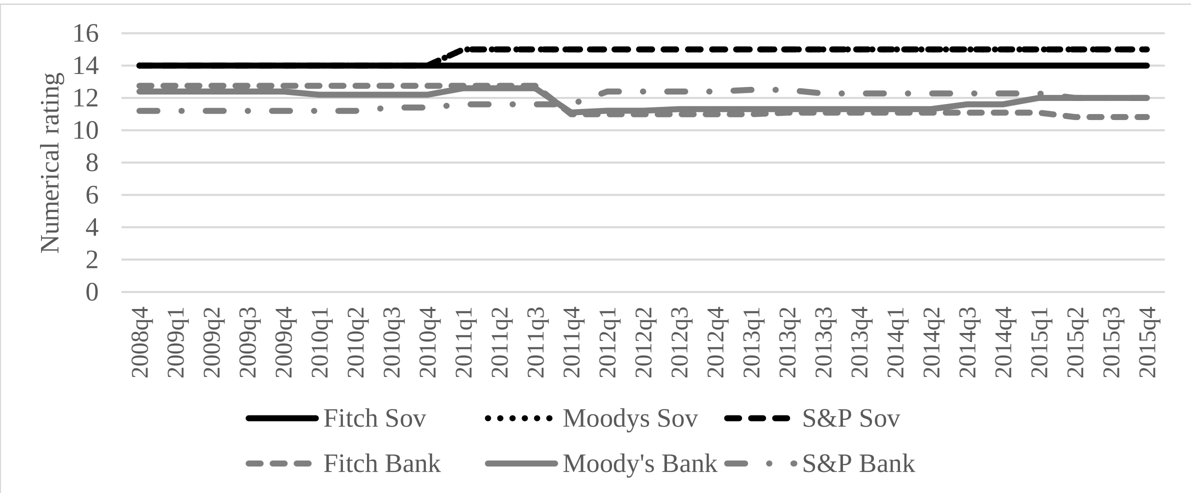


Figure C. China sovereign ratings vs. Average bank ratings



(Continued on next page)

Figure 6.2 (Continued)

Figure D. Indonesia sovereign ratings vs. Average bank ratings

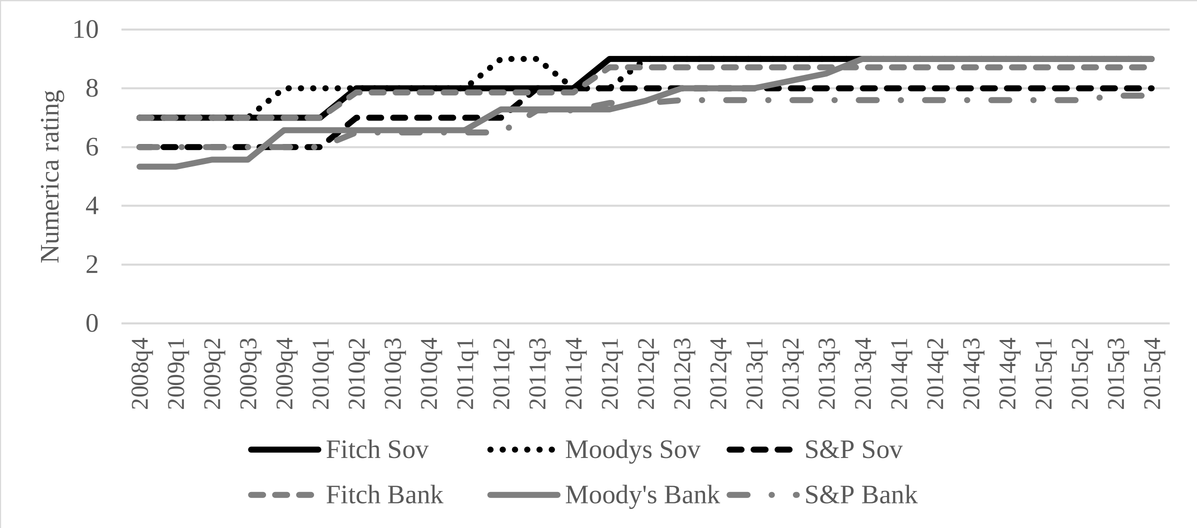


Figure E. Kazakhstan sovereign ratings vs. Average bank ratings

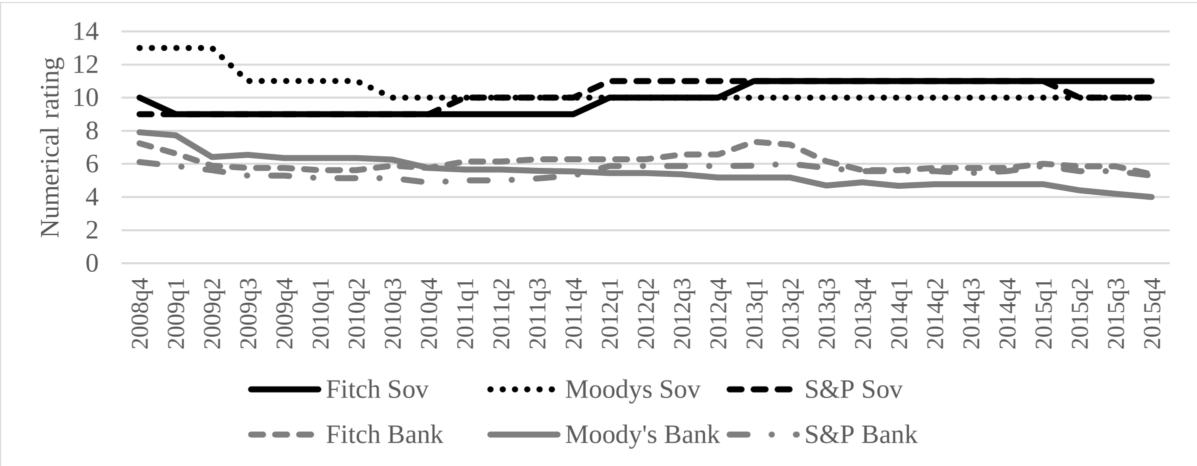
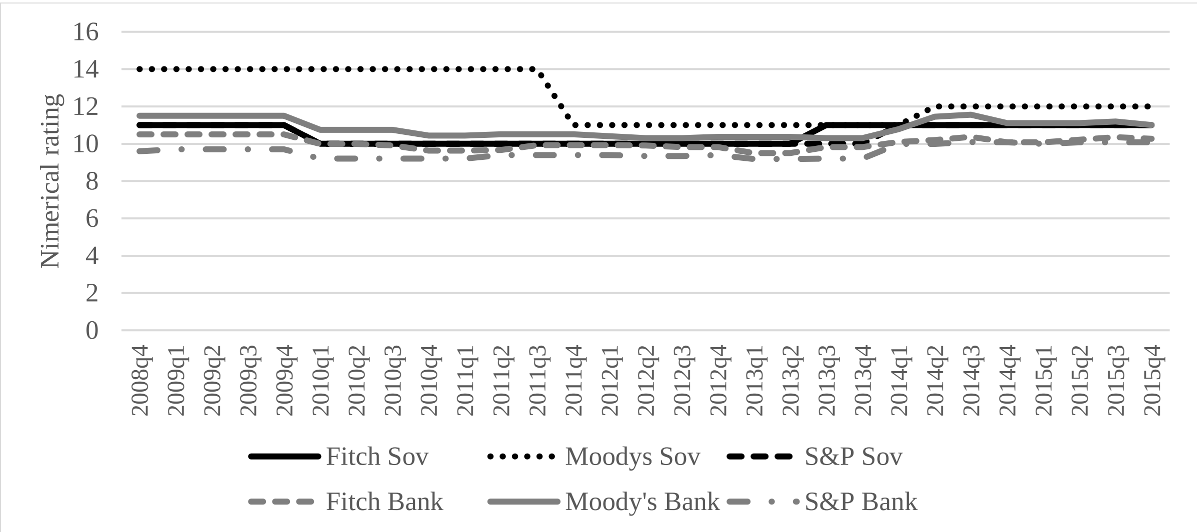


Figure F. Mexico sovereign ratings vs. Average bank ratings



(Continued on next page)

Figure 6.2 (Continued)

Figure G. Nigeria sovereign ratings vs. Average bank ratings

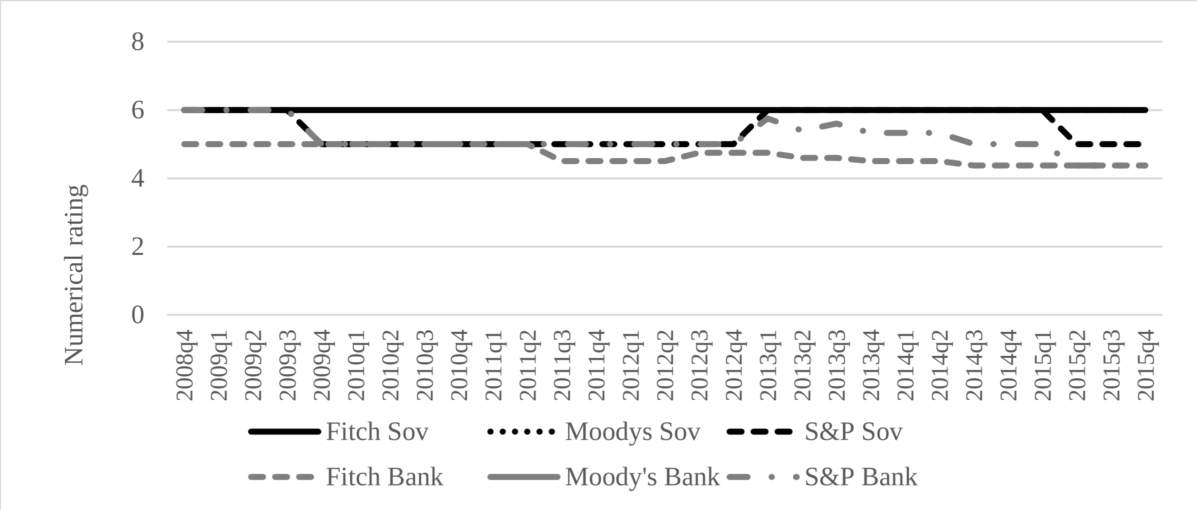


Figure H. Russia sovereign ratings vs. Average bank ratings

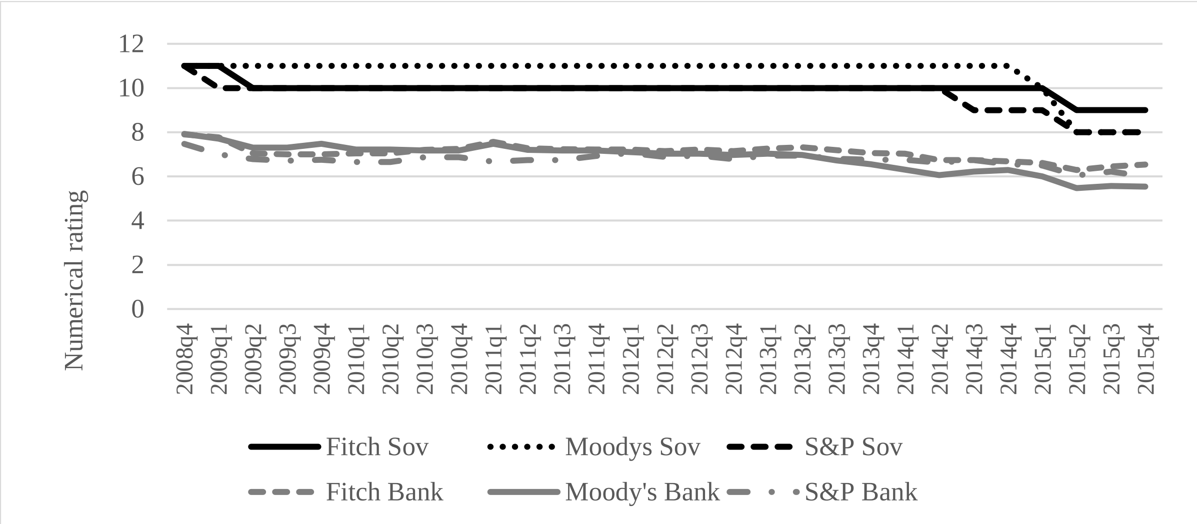
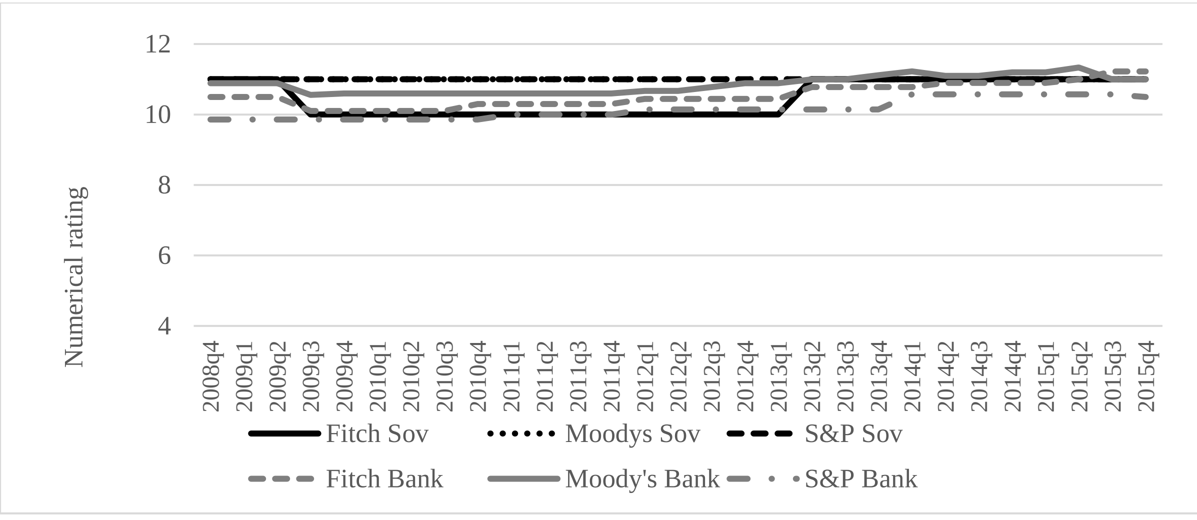


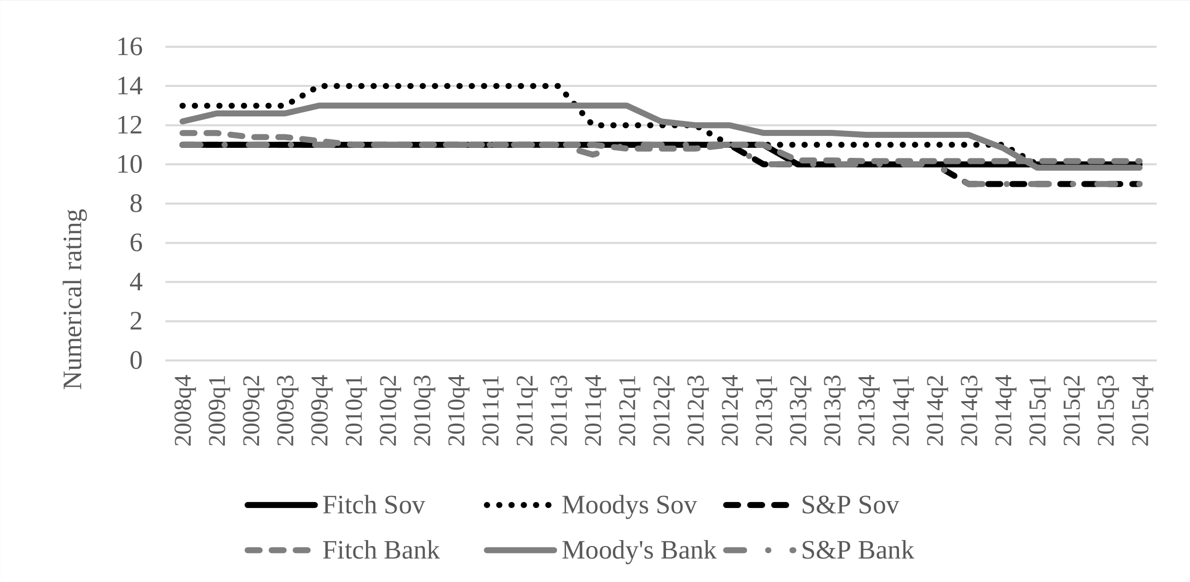
Figure I. Thailand sovereign ratings vs. Average bank ratings



(Continued on next page)

Figure 6.2 (Continued)

Figure J. South Africa sovereign ratings vs. Average bank ratings



The figures present the evolution of the quarterly long-term sovereign ratings assigned by S&P, Moody's and Fitch and the average bank ratings assigned by the three GRAs during October 2008 to December 2015. Sovereign and bank ratings are transformed according to an 18-point numerical scale. There is no information available in ID-CREM on Colombian bank ratings before the last quarter of 2011. Nigeria only has bank ratings assigned by Moody's in the last quarter of 2015.

Appendix

Table A 6.1 Superior S&P bank ratings than Moody's -including interaction terms

Variable	Dependent variable: *BSSup*			
	Eq (6.3)	Definition of ME	ME (%)	
			1	2
SSInf	-0.44***		0.24	0.05
	(-2.80)			
SSup	-0.11			
	(-0.45)			
CeSP	1.44***		0.29	0.27
	(8.07)			
CeM	-2.92***			
	(-10.30)			
SSInf*CeSP	-0.86***	ME for interaction SSInf and CeSP=1	0.01	-0.32
	(-3.78)	ME for interaction SSInf and CeSP=0	-0.08	-0.04
Observations	750			
Pseudo R-Squared	19.9%			
Country FE	Yes			
Year FE	Yes			

*The table reports the results of ordered probit estimations (Eq. (6.3)) using quarterly data from S&P and Moody's. The dependent variable **BSSup** denotes split bank ratings (of one-notch or two-or-more-notches), where S&P assigns superior bank ratings than Moody's. The key independent variable is **SSInf*CeSP**, defined as the interaction between the split sovereign dummy variable when S&P assigns inferior sovereign ratings than Moody's (SSinf), and S&P sovereign ceiling dummy variable (CeSP). See details of the explanatory variables in Sections 6.5.1 and 6.5.2. Full sets of country and year dummies are included. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. For detail on the marginal effects (ME) of the interaction terms see Section 6.5.2).*

Table A 6.2 Superior S&P bank ratings than Fitch – Including interaction terms

	Dependent variable: *BSSup*			
Variable	Eq (6.3)	Definition of MEs	ME%	
			1	2
SSInf	-0.06			
	(-0.26)			
SSup	0.93***		0.32	0.16
	(3.25)			
CeSP	-0.10			
	(-0.82)			
SSInf*CeSP	-0.24			
	(-0.82)			
SSup*CeSP	0.75*	ME for interaction SSup and CeSP=1	0.22	0.21
	(1.73)	ME for interaction SSup and CeSP=0	0.14	0.09
Observations	1,013			
Pseudo R-Squared	21.8%			
Country FE	Yes			
Year FE	Yes			

The table reports the results of ordered probit estimations (Eq. (6.3)) using quarterly data from S&P and Fitch. The dependent variable ***BSSup*** *denotes split bank ratings (of one-notch or two-or-more-notches), where S&P assigns superior bank ratings than Fitch. The key independent variable is* ***SSup*CeSP****, defined as the interaction between the split sovereign dummy variable when S&P assigns superior sovereign ratings than Fitch (SSup), and S&P sovereign ceiling dummy variable (CeSP). See details of the explanatory variables in Sections 6.5.1 and 6.5.2. Full sets of country and year dummies are included. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. For detail on the marginal effects (ME) of the interaction terms see Section 6.5.2).*

Table A 6.3 Superior Moody's bank ratings than Fitch -Including interaction terms

	Dependent variable: *BSSup*			
Variable	Eq (6.3)	Definition of ME	ME%	
			1	2
SSInf	-2.15***		0.27	0.18
	(-5.23)			
SSup	0.08			
	(0.61)			
CeM	1.09***			
	(7.36)			
CeF	-1.85***		0.31	0.05
	(-12.93)			
SSInf*CeF	3.61***	ME for interaction SSInf and CeF=1	0.18	0.22
	(5.10)	ME for interaction SSInf and CeF=0	-0.33	-0.26
SSup*CeM	0.19			
	(0.95)			
SSup*CeF	0.59***	ME for interaction SSup and CeF=1	0.16	0.05
	(3.13)	ME for interaction SSup and CeF=0	-0.02	0.05
Observations	1,728			
Pseudo R-Squared	21.7%			
Country FE	Yes			
Year FE	Yes			

The table reports the results of ordered probit estimations (Eq. (6.3)) using quarterly data from Moody's and Fitch. The dependent variable ***BSSup*** *denotes split bank ratings (of one-notch or two-or-more-notches), where S&P assigns superior bank ratings than Moody's. There are two key independent variables:* ***SSInf*CeF****, defined as the interaction between the split sovereign dummy variable when Moody's assigns inferior ratings than Fitch (SSinf), and Fitch sovereign ceiling dummy variable (CeF, and* ***SSup*CeF*** *defined as the interaction between the split sovereign dummy variable when Moody's assigns superior ratings than Fitch (SSinf), and Fitch sovereign ceiling dummy variable (CeF). See details of the explanatory variables in Sections 6.5.1 and 6.5.2. Full sets of country and year dummies are included. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. For detail on the marginal effects (ME) of the interaction terms see Section 6.5.2).*

Table A 6.4 Inferior S&P bank ratings than Moody's – Including interaction terms

	Dependent variable: *BSInf*			
Variable	Eq (6.4)	Definition of ME	ME%	
			1	2
SSInf	0.30**		0.56	0.23
	(2.29)			
SSup	-1.73***			
	(-7.69)			
CeSP	-1.78***			
	(-13.05)			
CeM	1.05***		0.45	0.41
	(8.72)			
SSInf*CeSP	0.03			
	(0.19)			
SSInf*CeM	1.08***	ME for interaction SSInf and CeM=1	-0.13	0.35
	(6.06)	ME for interaction SSInf and CeM=0	0.05	0.03
Observations	1,625			
Pseudo R-Squared	25.1%			
Country FE	Yes			
Year FE	Yes			

The table reports the results of ordered probit estimations (Eq. (6.4)) using quarterly data from S&P and Moody's. The dependent variable ***BSInf*** *denotes split bank ratings (of one-notch or two-or-more-notches), where S&P assigns inferior bank ratings than Moody's. The key independent variable is* ***SSInf*CeM****, defined as the interaction between the split sovereign dummy variable when S&P assigns inferior sovereign ratings than Moody's (SSinf), and Moody's sovereign ceiling dummy variable (CeM). See details of the explanatory variables in Sections 6.5.1 and 6.5.2. Full sets of country and year dummies are included. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. For detail on the marginal effects (ME) of the interaction terms see Section 6.5.2).*

Table A 6.5 Inferior S&P bank ratings than Fitch – Including interaction terms

	Dependent variable: *BSInf*			
Variable	Eq (6.4)	Definition of ME	ME%	
			1	2
SSInf	1.26***		0.40	0.37
	(8.35)			
SSup	-0.16			
	(-0.90)			
CeSP	-1.43***		0.25	0.70
	(-12.66)			
CeF	1.88***		0.42	0.28
	(15.05)			
SSInf*CeSP	-0.71*	ME for interaction SSInf and CeSP=1	0.08	0.22
	(-1.92)	ME for interaction SSInf and CeSP=0	-0.14	0.41
SSInf*CeF	1.29***	ME for interaction SSInf and CeF=1	-0.16	0.52
	(3.31)	ME for interaction SSInf and CeF=0	0.16	0.08
SSup*CeF	-1.40***	ME for interaction SSup and CeF=1	0.15	-0.25
	(-6.06)	ME for interaction SSup and CeF=0	-0.03	-0.01
Observations	1,561			
Pseudo R-Squared	27.8%			
Country FE	Yes			
Year FE	Yes			

*The table reports the results of ordered probit estimations (Eq. (6.4)) using quarterly data from S&P and Fitch. The dependent variable **BSInf** denotes split bank ratings (of one-notch or two-or-more-notches), where S&P assigns inferior bank ratings than Fitch. The key independent variables are: **SSInf*CeSP**, defined as the interaction between the split sovereign dummy variable when S&P assigns inferior sovereign ratings than Fitch (SSinf), and S&P sovereign ceiling dummy variable (CeSP); **SSInf*CeF**, defined as the interaction between the split sovereign dummy variable when S&P assigns inferior sovereign ratings than Fitch (SSinf), and Fitch sovereign ceiling dummy variable (CeF); and **SSup*CeF**, defined as the interaction between the split sovereign dummy variable when S&P assigns superior sovereign ratings than Fitch (SSup), and Fitch sovereign ceiling dummy variable (CeF). See details of the explanatory variables in Sections 6.5.1 and 6.5.2. Full sets of country and year dummies are included. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. For detail on the marginal effects (ME) of the interaction terms see Section 6.5.2).*

Table A 6.6 Inferior Moody's bank ratings than Fitch – Including interaction terms

	Dependent variable: *BSInf*			
Variable	Eq (6.4)	Definition of ME	ME% 1	ME% 2
SSInf	0.16			
	(0.89)			
SSup	-0.67***		0.28	0.13
	(-4.73)			
CeM	-2.97***		0.15	0.03
	(-17.45)			
CeF	2.72***		0.24	0.44
	(14.38)			
SSup*CeM	1.55***	MEs for interaction SSInf and CeM=1	-0.01	-0.01
	(7.61)	MEs for interaction SSInf and CeM=0	0.10	-0.37
SSInf*CeF	0.79***	MEs for interaction SSInf and CeF=1	-0.03	0.18
	(2.95)	MEs for interaction SSInf and CeF=0	0.02	0.02
SSup*CeF	-1.17***	MEs for interaction SSup and CeF=1	0.17	-0.29
	(-5.62)	MEs for interaction SSup and CeF=0	-0.07	-0.08
Observations	1,432			
Pseudo R-Squared	28.7%			
Country FE	Yes			
Year FE	Yes			

The table reports the results of ordered probit estimations (Eq. (6.4)) using quarterly data from Moody's and Fitch. The dependent variable ***BSInf*** *denotes split bank ratings (of one-notch or two-or-more-notches), where Moody's assigns inferior bank ratings than Fitch. The key independent variables are:* ***SSup*CeM****, defined as the interaction between the split sovereign dummy variable when Moody's assigns superior sovereign ratings than Fitch (SSup), and Moody's sovereign ceiling dummy variable (CeM);* ***SSInf*CeF****, defined as the interaction between the split sovereign dummy variable when Moody's assigns inferior sovereign ratings than Fitch (SSinf), and Fitch sovereign ceiling dummy variable (CeF); and* ***SSup*CeF****, defined as the interaction between the split sovereign dummy variable when Moody's assigns superior sovereign ratings than Fitch (SSup), and Fitch sovereign ceiling dummy variable (CeF). See details of the explanatory variables in Sections 6.5.1 and 6.5.2. Full sets of country and year dummies are included. Huber–White robust standard errors applied, and z-statistics reported beneath each coefficient. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. For detail on the marginal effects (ME) of the interaction terms see Section 6.5.2).*

Chapter 7 Conclusions

7.1 Conclusions

This thesis aims to investigate the determinants of GRAs' rating assignments for emerging market banks. It uses three different approaches. The first approach compares the drivers of S&P NSR and GSR assignments and studies the dynamics and divergence between those two types of ratings. The second approach examines the effects of bank opacity on split bank ratings between GRAs and rating migrations. The third approach studies the systematic component of split bank ratings by considering opacity at the sovereign government level alongside the effect of the sovereign rating ceiling. Each of the approaches provides highly original insights and thereby the thesis offers substantial contributions to the academic literature.

Credit ratings have a significant effect on debt issuers' cost of borrowing and influence the decision-making process of market participants. Internationally, credit ratings are used in the calculation of the minimum capital requirements, are part of the regulatory investment limits imposed on institutional investors and are used to evaluate investment portfolios. Studies on bank credit ratings are mainly focused on GRAs because these have the largest market share and a good historical reputation (see Section 3.2.1). Furthermore, the studies on GRAs are mainly conducted with data from developed economies, most likely because researchers have access to high quality information and have the possibility of cross-country comparisons as the studies are usually based on global scale ratings. The recent expansion of the GRAs' presence in emerging economies has increased the scope of the credit rating literature which uses data from emerging economies (see Section 3.1). Nevertheless, considering the importance of the potential research questions, this literature is very thin and most studies are based on one country. The few existing studies show that the expansion of GRAs in emerging economies has been achieved mainly through affiliates and joint ventures (indirect presence), as several emerging countries have regulatory limitations that prevent or discourages GRAs from operating directly in the markets (e.g. South Korea, China).

These prior studies offer diverse views on the relevance of GRAs and NRAs. However, they tend to highlight that GRAs are strong competitors of NRAs in the domestic markets through their national ratings, which incorporate the reputational value of the GRAs. The literature, however, has neglected the fact that GRAs can assign both national and global scale ratings and that there is possibly a strong dynamic between them. Considering both types of ratings from the same GRA challenges the viewpoint about the segmentation of the credit rating industry suggested by Ferri and Lacitignola (2010) in the Asian market because they omit the national ratings assigned by GRAs.

In addition, the limited literature on national scale ratings has neglected the study of the banking industry in emerging economies and has mostly focused on non-financial corporates. Investigating national ratings in the banking industry is highly relevant, considering that the banking industry fulfils an essential role as a provider of funding in emerging economies. This is particularly pertinent because information asymmetries between issuers and investors are more significant in emerging economies. These asymmetries, along with strong financial constraints faced by domestic companies, increase the number of bank borrowers and somewhat restrain companies from seeking funding in the debt or equity security markets (Nagano, 2018).

Furthermore, the sovereign government's opacity and weak institutional frameworks observed in emerging economies play a significant role in companies' funding decisions. Namely, opaque companies prefer to borrow via bank loans rather than seek funding in the capital markets because the monitoring exerted by banks and the government is typically less intrusive or severe than the CRA and investor monitoring which applies to bond issuers. These particular features of the banking industry of emerging economies are more challenging to evaluate by CRAs and imply that in these countries GRAs are exposed to higher uncertainty when assigning bank ratings compared to rating assignments in other sectors. Following the prior split ratings literature (e.g. Morgan, 2002; Iannotta, 2006), higher opacity in the banking industry should lead to a higher proportion of rating disagreements. Thus, split bank ratings could be significantly more common in emerging economies compared to developed economies, although there is no substantial prior evidence on this in the credit rating literature. Furthermore, Livingston et al. (2008) and Alsakka and ap Gwilym (2010c) show that when an issuer (issue) has split ratings, it is more likely that it experiences future rating actions, and that, because of opacity, harsher split ratings increase the probability of those future rating changes (see Section 3.2.4). Thus, it is highly likely to find a strong link between split bank ratings and bank rating migrations due to banks' opacity in emerging economies.

From a different perspective, split bank ratings can also be driven by a systematic element e.g. opacity in the sovereign government's ability and willingness to meet debt obligations in a timely and complete manner. The strong link between sovereign risk and bank risk has been broadly recognised by academics (see Section 6.2.3). One focus of research has been the transmission of the sovereign risk to the banking industry through the rating channel (e.g. Williams et al., 2013, 2015; Alsakka et al., 2014; Huang and Shen, 2015; Drago and Gallo, 2017; Klusak et al., 2017). Specifically, the literature shows that sovereign rating actions have a significant effect on bank rating actions, and the link is particularly relevant for banks with ratings equal to or higher than sovereign ratings. However, the effect of sovereign risk has not been incorporated into the few prior studies of split bank ratings. In emerging economies, sovereign risk is related to low government transparency and political instability (see Sections 6.2.3 and 6.24). These aspects influence bank risk-taking behaviour and increase the opacity of the banking industry. However, the literature on split bank ratings has not incorporated sovereign opacity as one of the potential drivers of rating disagreements. This void arises because the previous studies are based on data from developed economies, where the government opacity is a far less significant issue than in emerging economies.

Given the above motivations to undertake this research, the particular aims of each of the chapters of the thesis are as follows. Chapter 4 studies the information content of ratings by focusing on the drivers of national and global scale ratings assigned by S&P, covering an angle of GRAs' activities which was unexplored by prior credit rating literature. Chapter 5 investigates the determinants of split bank ratings in emerging economies, to shed light on the level of opacity in the banking industry and how that affects the rating decisions of the GRAs. Additionally, Chapter 5 analyses the effect of opacity upon future rating changes, using split bank ratings between GRAs as a proxy of opacity. Chapter 6 explores whether split bank ratings are driven by a systematic component i.e. split sovereign ratings, to better understand the effect of political risk and information asymmetries in GRAs' bank rating decisions.

Chapter 4 examines an original research question: 'what are the drivers of the bank ratings assigned by S&P in emerging economies?'. The uniqueness of the study is its focus on both national and global scale ratings assigned by the same GRA. This approach has not been applied in any prior literature. The sample comprises 4,284 bank-quarter observations,[150] where 145 banks from 11 emerging economies have long-term global scale ratings (GSR) and long-term national scale ratings (NSR) assigned by S&P during the period of 2006 to 2015. The rating data is matched with financial ratios employed as potential drivers, including: bank size, capital ratio, asset quality, trading (non-interest income), profitability (net interest), efficiency, cost of debt and liquidity. To examine the drivers of each type of rating and the dynamics between both types of ratings, five sub-samples are considered (for a full description, see Table 4.6). To address the propensity to have a national or a global rating assigned by S&P, Chapter 4 incorporates a binary probit approach, which is commonly used in credit rating literature (Morgan, 2002; Bowe and Larik, 2014).

The results of Chapter 4 show that banks with a larger size, higher profitability, and higher liquidity have a higher probability of being assigned a GSR. Smaller size banks, with lower liquidity and

[150] Refers to the total sample, including 145 rated banks with long-term issuer national and/or global scale ratings and 275 banks not rated by S&P.

higher loan quality, have a higher likelihood of being assigned an NSR. Moreover, the results of Chapter 4 show that assigning an NSR is more likely than a GSR in countries where global bank ratings are tightly close to sovereign ratings. The possible explanation for this is that NSR are more informative on the idiosyncratic bank risk than GSR because the latter are highly influenced by sovereign ratings in emerging economies, as shown for corporates by Ferri (2004). Further, when prior S&P ratings are included, the results show that larger banks with prior NSR (GSR) by S&P have less probability of being assigned a GSR (an NSR) in the period of analysis. If an NS-rated bank is cross-listed and has foreign ownership, there is a higher probability of being assigned a GSR, while GS-rated cross-listed banks are less likely to be assigned an NSR. The competition between GRAs also influences the probability of being assigned an S&P rating. While the probability of being rated by S&P in NSR or GSR increases if the bank has prior ratings by Moody's, having a rating assigned by Fitch increases only the likelihood of being assigned a GSR by S&P. Also, the robustness test suggests that S&P's reputation diminished during the financial crisis of 2007-2009, as banks have a lower probability of being rated by S&P during that period than being unrated. These findings provide completely original insights into the strong interrelation between NSR and GSR.

Chapter 5 investigates two research questions: 'What are the drivers of GRAs' split bank ratings?' and 'What is the effect of split bank ratings on the future bank rating migrations?'. A panel dataset of 862 observations (78 banks) with global ratings assigned by S&P and Moody's, 798 observations (76 banks) with global ratings assigned by S&P and Fitch, and 813 observations (64 banks) with global ratings assigned by Moody's and Fitch (813) from 10 emerging countries,[151] during October 2008 to December 2015 is used. Chapter 5 addresses the determinants of split bank ratings and the influence on future rating migrations using a binary probit model because, in the sample, the most common case by far is one-notch split ratings. The methodological approach is coherent with prior split ratings literature (Morgan, 2002; Livingston et al., 2008, 2010; Bowe and Larik, 2014). Because observations with split ratings of more-than-one-notch between two GRAs represent on average 23.0% of cases, an ordered probit model is also used, which is also a common approach in the ratings literature (e.g. Iannotta, 2006; Livingston et al., 2007; Alsakka and ap Gwilym, 2010c; Vu et al., 2017). The analysis of the drivers of split ratings tests the *opacity hypothesis* that asserts that split ratings between GRAs are not a result of random errors in the rating process but are related to GRAs' response to opacity (See Section 3.2.4).

[151] For S&P and Moody's, and for Moody's and Fitch, the sample comprises banks from 9 countries, excluding Argentinean and Nigerian banks, and for S&P and Fitch, the sample includes bank ratings from 10 countries, excluding Argentinean banks (see further details in Section 5.4.3).

The results of the first part of Chapter 5 suggest that split bank ratings between GRAs are driven by the bank's asset opacity rather than by random errors in the rating process. Among the proxies of opacity, larger bank size and a high level of capital, increase the probability of split ratings between S&P and Moody's. For S&P and Fitch, only bank size significantly impacts the probability of split ratings. For Fitch and Moody's, split ratings are more likely to occur when the bank has lower profitability and, to a lesser extent, lower liquidity. A lower level of government transparency has a significant influence on rating disagreements between S&P and Moody's, while split ratings between S&P and Fitch have less likelihood of occurring in countries with greater financial depth. Banks with investment grade ratings have a lower probability of having split ratings between S&P and Moody's and between Moody's and Fitch. Furthermore, the sample used in the Chapter suggests that S&P is the most conservative GRA, in contrast with prior literature that finds that Moody's is more conservative than S&P in split bank ratings (Morgan, 2002; Iannotta, 2006). When investigating the causes of rating conservativeness, the evidence suggests that larger banks are more likely to be rated lower by S&P, while Moody's tends to be less conservative than Fitch when the profitability is higher.

The second part of Chapter 5 suggests that split bank ratings between GRAs influence future rating changes. In particular, the effects of rating disagreements are significantly stronger on rating upgrades than on downgrades. Banks are more likely to be upgraded in the following quarter by the GRA that assigned previously a lower rating and of being downgraded by the GRA that assigned the higher rating. Moreover, wider split bank ratings (in notches) induce stronger effects on the likelihood of rating changes. Split ratings between Fitch and S&P influence each other's rating migrations. Moody's is the less influential when rating disagreements occur with S&P. When Moody's assigns a bank rating higher than S&P, the likelihood of S&P upgrading the bank in the next quarter is higher. However, when Moody's is more conservative, it does not have any effect on future S&P rating changes. When Fitch is more (or less) conservative than Moody's, the likelihood of future rating upgrades (or downgrades) by Moody's is higher, while Moody's superior or inferior ratings have no effect on Fitch's future rating changes.

Chapter 6 examines whether split sovereign ratings influence split bank ratings and if they can be considered as the systematic component of split bank ratings in emerging economies. A panel dataset of 1,901 observations (95 banks) from 9 countries with global ratings assigned by S&P and Moody's; 1,772 observations (95 banks) from 10 countries with global ratings assigned by S&P and Fitch; and 2,425 observations (113 banks) from 11 countries with global ratings assigned by

Moody's and Fitch, during 2008 to 2015, is used.[152] The Chapter employs an ordered probit modelling approach, commonly used in the split ratings literature (see Section 6.5.1). Split sovereign ratings are employed as a measure of the systematic factors to capture the effect of the sovereign opacity and evaluate the rating channel for transmission of sovereign risk to bank risk. There is also separate treatment of inferior and superior ratings, because prior literature shows that one GRA tends to assign more conservative ratings than the other, depending on the countries and data under investigation (see Section 3.2.4). This separation allows evaluation of whether the tendency to assign conservative bank ratings conveys the same behaviour in sovereign ratings, when rating disagreements occur. Additionally, the sovereign ceiling effect[153] is included as a driver of the split bank ratings, because bank ratings are often bounded by the sovereign rating in emerging economies (see Section 6.2.3) and that the timing of sovereign and bank rating changes differs between GRAs when the ceiling effect is influential (Huang and Shen, 2015).

The results from Chapter 6 suggest that sovereign opacity, proxied by sovereign rating disagreements, has a significant influence on split bank ratings in emerging economies. The ceiling effect also has a significant impact on split bank ratings, suggesting that both split sovereign ratings and the ceiling effect are pertinent in capturing a systematic component of split bank ratings. The descriptive statistics show that S&P tends to assign more conservative bank ratings and sovereign ratings than Moody's and Fitch. Among Moody's and Fitch, the latter is more conservative in both bank and sovereign ratings. The tendency to assign conservative sovereign ratings increases the likelihood of assigning lower bank ratings when split ratings occur. The probabilities of S&P assigning inferior bank ratings than Fitch, when S&P assigns inferior sovereign ratings than Fitch are stronger than for split bank ratings between S&P and Moody's or between Moody's and Fitch. Moreover, the results show that, although GRAs no longer strictly apply the sovereign rating ceiling rule for all cases, the effects of sovereign split ratings on split bank ratings are more significant when the ceiling effect takes place. This is particularly true when split bank ratings are of two or more notches. S&P assigning inferior sovereign ratings has a greater impact on the probability of S&P assigning two-or-more-notches inferior bank ratings than Fitch (Moody's) when Fitch (Moody's) sovereign ceiling applies. Two-or-more-notches inferior Moody's sovereign ratings increase the likelihood of Moody's assigning inferior bank ratings when Fitch ceiling effect occurs.

[152] For S&P and Moody's Argentinean and Nigerian banks are excluded from the sample. For S&P and Fitch, Argentinean banks are excluded since are not rated by both S&P and Fitch (see further details in Section 5.4.3).

[153] Chapter 6 incorporates the ceiling effect by including a dummy variable that takes the value of one when the bank rating is equal or higher than the sovereign rating assigned by a GRA.

This thesis contributes new insights to the credit rating literature in several ways. Chapter 4 is the first study on the drivers of NSR and GSR assigned by a single CRA. It benefits substantially from the construction of a unique dataset of S&P NSR and GSR assignments, which is matched with financial and accounting variables. Secondly, the research design used in Chapter 4 enables the study of the drivers of NSR ratings in a cross-country setting, which is unique in the literature. The scarce prior research incorporating national scale ratings involves country-specific cases (e.g. Bissoondoyal-Bheenick and Treepongkaruna, 2011; Ferri et al., 2013; Livingston et al., 2018). Chapter 5 offers insights on bank opacity in emerging economies and provides a unique perspective on how the opacity impacts split bank ratings and rating migrations. These topics were both unexplored in the prior split ratings literature and have practical economic relevance due to the important role of the banking sector in emerging economies. Chapter 5 also contributes to the split ratings literature by incorporating the effects of bank opacity on GRAs' assignments of superior or inferior ratings, which has only been studied in US corporates by Bowe and Larik (2014). Chapter 6 takes a novel perspective on split bank ratings by examining the effect of a systematic component e.g. the sovereign risk, on bank rating disagreements. Moreover, by employing sovereign split ratings, the thesis incorporates the effect of political risk and information disclosure (see Vu et al., 2017), which are particularly relevant in emerging economies. Furthermore, by incorporating the interaction between split sovereign ratings and the ceiling effect, the chapter sheds light on how sensitive are split bank ratings to sovereign rating disagreements when the ceiling effect takes place, an aspect that has not been studied before by academia.

Chapter 4 benefits substantially from the construction of a unique dataset of S&P NSR and GSR assignments, which is matched with financial and accounting variables. The research design used in Chapter 4 also enables the study of the drivers of NSR ratings in a cross-country setting, which is unique in the literature. The scarce prior research incorporating national scale ratings involves country-specific cases (e.g. Bissoondoyal-Bheenick and Treepongkaruna, 2011; Ferri et al., 2013; Livingston et al., 2018c). Chapter 4 also contributes new insights to the credit rating literature in several ways. Firstly, the thesis suggests that S&P's NSR carry the same reputational value as S&P's GSR for banks in emerging economies. Therefore, from a novel perspective, this thesis supports the strong certification effect of GRAs' ratings found by the rating literature (Poon and Chan, 2008; Deb et al., 2011; Bongaerts et al., 2012). Chapter 4 also contributes to the debate of market segmentation between NRAs and GRAs (see Ferri and Lacitignola, 2010; Marandola, 2016), by showing that S&P's NSR and GSR have a strong interdependency. This suggests that the segmentation between GRAs and NRAs assigning GSR and NSR, respectively, might have very limited relevance once NSR from GRAs are incorporated. Lastly, Chapter 4 contributes to the discussion of the effects of competition between GRAs presented in the literature (see Becker and Milbourn, 2011; Bongaerts et al., 2012), showing that Fitch and Moody's ratings have a strong impact on S&P rating assignments, in both GSR and NSR.

Chapter 5 reveals new insights into bank opacity in emerging economies. Firstly, the results show a higher proportion of split bank ratings compared to the percentage reported for the US by Morgan (2002). This suggests that GRAs perceive higher uncertainty in the banking industry in emerging economies compared to the same sector in developed markets. Secondly, the Chapter supports the literature that suggests that bank characteristics, as proxies of opacity, influence bank splits in emerging economies. However, unlike Morgan (2002) and Iannotta (2006), the drivers of split bank ratings are studied for all three GRAs, and for inferior versus superior bank ratings. Thus, the Chapter contributes with new evidence on the sensitivities of bank rating disagreements to the opacity proxies, which appears to vary between each pair of GRAs and among bank characteristics. The conservative behaviour in ratings observed by S&P compared to Moody's or Fitch is triggered mainly by the complexity of the bank business and the bank's type of ownership. Thirdly, while S&P and Fitch split ratings tend to influence each other's rating changes, split ratings between Moody's and S&P/Fitch have little influence on S&P or Fitch rating migrations. In contrast, Moody's rating migrations are highly sensitive to split ratings between Moody's and S&P or Fitch. Thus, although it is not tested explicitly, the Chapter raises questions on the conservative rating behaviour of S&P versus the effects of competition or reputation as a potential explanation of rating migrations (see e.g. Lugo et al., 2015 and Güttler, 2011).

Chapter 6 takes a novel perspective on split bank ratings by examining the effect of split sovereign ratings and the sovereign ceiling, as systematic factors that might explain bank rating disagreements. The Chapter shows that bank rating disagreements are highly sensitive to sovereign split ratings and the sovereign ceiling for all pairs of GRAs. However, the sensitivity to these factors differs for the GRA that assigns inferior or superior bank ratings. Therefore, the Chapter proposes an alternative method of examining the rating channel of transmission for sovereign risk to bank ratings, which previously has been studied through sovereign rating changes and its effects on bank ratings (see Williams et al., 2013, 2015; Huang and Shen, 2015). Moreover, the literature suggests that the sovereign ceiling has a significant effect on bank ratings (Williams et al., 2013; Adelino and Ferreira, 2016; Drago and Gallo, 2017). The results also reveal asymmetries in the sensitivities of inferior and superior bank ratings to split sovereign ratings when the ceiling effect of the competitor GRA occurs. This implies that besides asset or government opacity, the competition between GRAs has a substantial role in explaining bank rating disagreements, an issue that has not been examined by the literature yet.

One of the implications of Chapter 4 is that GRAs can be a strong competitor of NRAs in the domestic markets, although the advantage of GRAs' rating assignments is more noticeable for larger banks. If that is the case, GRAs' reputation (certification effect) could cause distortions in the information content of NSR and potentially reduce the value of ratings assigned by NRAs, which is a topic relevant for regulations and bank supervisors. Therefore, future research could examine the competition at the domestic level between GRAs' NSR and bank ratings assigned by NRAs. Moreover, future research can examine the impact of NSR in domestic bond yields and to investigate whether domestic investors differentiate when banks (or corporates) have both types of ratings. There is also scope for related studies of NSR to address structured finance transactions and other asset types.

For policymakers, the results of Chapter 5 imply that market discipline in emerging economies may not be sufficient to reduce risk-taking behaviour in banks nor to induce greater transparency. Policies focused on reducing asset opacity, such as the improvement of the monitoring of borrowers, could have a positive impact on bank stability. A decrease in bank rating disagreements would signal a lower bank opacity. Moreover, S&P's tendency to assign lower bank ratings than the competitor GRA in emerging economies is a valuable source of information for investors, who face large information asymmetries in these countries. However, if investors associate S&P's rating conservativeness with better rating quality, the results of Chapter 5 should be relevant for S&P and the other GRAs, as an incentive to guard their market reputation and prevent rating arbitrage. Furthermore, the relevant effect of split bank ratings on future bank rating changes in emerging economies shows the importance of considering the influence of rating disagreements on rating transition matrices. Two potential new directions of research emerge from the findings and implications of Chapters 4 and 5. Firstly, since asset opacity can also affect NSR disagreements between GRAs, future studies can examine the drivers of split NSR in the banking sector of emerging economies. Secondly, the investigation of whether opacity premiums required by investors associated with NSR are evident in the domestic bond yields. Additionally, while this thesis underpins the important effect of bank opacity in split bank ratings in emerging economies, further research is needed on the effect of the implementation of international banking regulations (e.g. Basel III).

The results of Chapter 6 complement the findings in Chapter 5, showing that split bank ratings also reflect the high sovereign uncertainty perceived by GRAs in emerging economies. These results imply that countries that develop policies to tackle the corruption level and improve the institutional environment can thereby engender a more stable and resilient banking industry, which would be perceived as lower uncertainty in the risk assessment of GRAs. Furthermore, considering the significant sensitivity of split bank ratings to split sovereigns when the sovereign ceiling effect occurs, policies that prevent banks from holding a high proportion of public debt in their portfolios are relevant to avert a contagion effect when the government experiences fiscal distress (e.g. El Salvador). Considering the findings in Chapter 6, future investigations on bank issuances could address how sovereign splits and the sovereign ceiling are priced by investors in bank bonds. Also, considering the sensitivity of split bank ratings to sovereign splits if the ceiling effect of the competitor GRA occurs, further research could study the influence of competition between GRAs and reputation on the sensitivities of split ratings.

A key limitation of this research arises from the constraints placed upon it by the public availability of financial data for banks in emerging economies. For example, this reduces greatly the potential sample sizes after matching financial data with the rating data. The data restrictions are undesirable in some instances e.g. when estimating the drivers of S&P GSR assignments for NSR-rated banks. Also, while the use of only S&P ratings could place a limit on the significance of the results of Chapter 4, the inclusion of Fitch and Moody's bank ratings as potential drivers of S&P rating assignments does provide new insights on competition between GRAs. Furthermore, using financial variables as opacity measures instead of analysts' earnings forecasts (see Livingston et al., 2007; Livingston and Zhou, 2010, 2016), can increase the risk of using data susceptible to be manipulated by managers. There is also a consequent slant towards a historical view instead of a forward-view (Fosu et al., 2018). However, good quality data on analysts' earnings forecasts is not available for emerging economies, and even if it was available, the low information quality and low transparency of the institutions in emerging economies could also distort the analysts' opinions.

References

Acharya, V., Pedersen, L. H., Philippon, T. and Richardson, M. (2017) 'Measuring systemic risk', Review of Financial Studies, 30(1), pp. 2–47. doi: 10.1093/rfs/hhw088.

Adelino, M. and Ferreira, M. A. (2016) 'Bank ratings and lending supply: Evidence from sovereign downgrades', Review of Financial Studies, 29(7), pp. 1709–1746. doi: 10.1093/rfs/hhw004.

Afik, Z., Feinstein, I. and Galil, K. (2014) 'The (un)informative value of credit rating announcements in small markets', Journal of Financial Stability, 14, pp. 66–80. doi: 10.1016/j.jfs.2014.08.001.

Almeida, H., Cunha, I., Ferreira, M. A. and Restrepo, F. (2017) 'The real effects of credit ratings: The sovereign ceiling channel', Journal of Finance, 72(1), pp. 249–290. doi: http://dx.doi.org/10.2139/ssrn.2349051.

Alsakka, R., ap Gwilym, O., Klusak, P. and Tran, V. (2015) 'Market impact under a new regulatory regime: credit rating agencies in Europe', Economic Notes, 44(2), pp. 275–308. doi: 10.1111/ecno.12039.

Alsakka, R. and ap Gwilym, O. (2009) 'Heterogeneity of sovereign rating migrations in emerging countries', Emerging Markets Review, 10(2), pp. 151–165. doi: http://dx.doi.org/10.1016/j.ememar.2008.12.001.

Alsakka, R. and ap Gwilym, O. (2010a) 'A random effects ordered probit model for rating migrations', Finance Research Letters, 7(3), pp. 140–147. doi: http://dx.doi.org/10.1016/j.frl.2010.02.004.

Alsakka, R. and ap Gwilym, O. (2010b) 'Leads and lags in sovereign credit ratings', Journal of Banking & Finance, 34(11), pp. 2614–2626. doi: 10.1016/j.jbankfin.2010.05.001.

Alsakka, R. and ap Gwilym, O. (2010c) 'Split sovereign ratings and rating migrations in emerging economies', Emerging Markets Review, 11(2), pp. 79–97. doi: http://dx.doi.org/10.1016/j.ememar.2009.11.005.

Alsakka, R. and ap Gwilym, O. (2012) 'The causes and extent of split sovereign credit ratings in emerging markets', Emerging Markets Finance and Trade, 48(1), pp. 4–24. doi: 10.2753/REE1540-496X480101.

Alsakka, R., ap Gwilym, O. and Vu, H. (2017) 'Differences of opinion in sovereign credit signals during the European crisis', European Journal of Finance, 23(10), pp. 859–884. doi: 10.1080/1351847X.2016.1177565.

Alsakka, R., ap Gwilym, O. and Vu, T. N. (2014) 'The sovereign-bank rating channel and rating agencies' downgrades during the European debt crisis', Journal of International Money and Finance, 49, pp. 235–257. doi: 10.1016/j.jimonfin.2014.03.012.

Alsakka, R., ap Gwilym, O., Klusak, P. and Tran, V. (2015) 'Market impact under a new regulatory regime: credit rating agencies in Europe', Economic Notes, 44(2), pp. 275–308. doi: 10.1111/ecno.12039.

Altman, E. I. and Rijken, H. A. (2004) 'How rating agencies achieve rating stability', Journal of Banking & Finance, 28(11), pp. 2679–2714. doi: 10.1016/j.jbankfin.2004.06.006.

Altunbas, Y., Manganelli, S. and Marques-Ibanez, D. (2017) 'Realized bank risk during the great recession', Journal of Financial Intermediation, 32, pp. 29–44. doi: 10.1016/j.jfi.2017.08.001.

Amihud, Y. (2002) 'Illiquidity and stock returns: cross-section and time-series effects', Journal of Financial Markets, 5(1), pp. 31–56. doi: 10.1016/S1386-4181(01)00024-6.

Amstad, M. and Packer, F. (2015) 'Sovereign ratings of advanced and emerging economies after the crisis', BIS Quarterly Review, (December), pp. 77–91. Available at: https://www.bis.org/publ/qtrpdf/r_qt1512.htm.

Anginer, D., Demirgüç-Kunt, A. and Mare, D. S. (2018) 'Bank capital, institutional environment and systemic stability', Journal of Financial Stability, 37, pp. 97–106. doi: 10.1016/j.jfs.2018.06.001.

Arena, M. (2008) 'Bank failures and bank fundamentals: A comparative analysis of Latin America and East Asia during the nineties using bank-level data', Journal of Banking & Finance, 32(2), pp. 299–310. doi: 10.1016/j.jbankfin.2007.03.011.

Ashraf, B. N. (2018) 'Do trade and financial openness matter for financial development? Bank-level evidence from emerging market economies', Research in International Business and Finance, 44, pp. 434–458. doi: 10.1016/j.ribaf.2017.07.115.

Avendaño, R. and Nieto-Parra, S. (2015) 'What factors impact the cost of corporate bond issuance? A study of emerging primary markets', Corporate governance in Brazil, Chile, Colombia, Mexico and Peru: The determinants of risk in corporate debt issuance. ECLAC. (LC/W.654), pp. 85–105. Available at: http://repositorio.cepal.org/handle/11362/37721.

Aysun, U. and Hepp, R. (2016) 'The determinants of global bank lending: Evidence from bilateral cross-country data', Journal of Banking & Finance Finance, 66, pp. 35–52. doi: 10.1016/j.jbankfin.2015.11.020.

Bae, K.-H., Purda, L., Welker, M. and Zhong, L. (2013) 'Credit rating initiation and accounting quality for emerging-market firms', Journal of International Business Studies, 44(3), pp. 216–234. doi: 10.1057/jibs.2013.4.

Baele, L., De Jonghe, O. and Vander Vennet, R. (2007) 'Does the stock market value bank diversification?', Journal of Banking & Finance, 31, pp. 1999–2023. doi: 10.1016/j.jbankfin.2006.08.003.

Bakalyar, I. and Galil, K. (2014) 'Rating shopping and rating inflation in Israel', International Review of Financial Analysis, 33, pp. 270–280. doi: 10.1016/j.irfa.2014.03.005.

Baker, H. K. and Mansi, S. A. (2002) 'Assessing credit rating agencies by bond issuers and institutional investors', Journal of Business Finance & Accounting, 29(9–10), pp. 1367–1398. doi: 10.1111/1468-5957.00474.

Ballester, L. and González-Urteaga, A. (2017) 'How credit ratings affect sovereign credit risk: Cross-border evidence in Latin American emerging markets', Emerging Markets Review, 30, pp. 200–214. doi: 10.1016/j.ememar.2016.09.004.

Bannier, C. E., Behr, P. and Güttler, A. (2010) 'Rating opaque borrowers: why are unsolicited ratings lower?', Review of Finance, 14(2), pp. 263–294. doi: 10.1093/rof/rfp025.

Basel Committee (2000) Credit ratings and complementary sources of credit quality information, Bank for International Settlements, Basel Committee on Banking Supervision. Working Paper 3. Available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.139.6186&rep=rep1&type=pdf.

Bassett, W. F., Lee, S. J. and Spiller, T. P. (2015) 'Estimating changes in supervisory standards and their economic effects', Journal of Banking & Finance, 60, pp. 21–43. doi: 10.1016/j.jbankfin.2015.07.010.

Beaver, W. H., Shakespeare, C. and Soliman, M. T. (2006) 'Differential properties in the ratings of certified versus non-certified bond-rating agencies', Journal of Accounting and Economics, 42(3), pp. 303–334. doi: 10.1016/j.jacceco.2006.06.002.

Beccalli, E., Anolli, M. and Borello, G. (2015) 'Are European banks too big? Evidence on economies of scale', Journal of Banking & Finance, 58, pp. 232–246. doi: 10.1016/j.jbankfin.2015.04.014.

Becker, B. and Milbourn, T. (2011) 'How did increased competition affect credit ratings?', Journal of Financial Economics, 101(3), pp. 493–514. doi: 10.1016/j.jfineco.2011.03.012.

Behr, P., Kisgen, D. J. and Taillard, J. (2016) 'Did government regulations lead to inflated credit ratings?', Management Science, 64(3), pp. 1–55. doi: 10.2139/ssrn.2412294.

Bell, R. G., Filatotchev, I. and Rasheed, A. (2012) 'The liability of foreignness in capital markets: Sources and remedies', Journal of International Business Studies, 43(2), pp. 107–122. Available at: http://dx.doi.org/10.1057/jibs.2011.55.

Bellotti, T., Matousek, R. and Stewart, C. (2011) 'Are rating agencies' assignments opaque? Evidence from international banks', Expert Systems with Applications, 38(4), pp. 4206–4214. doi: 10.1016/j.eswa.2010.09.085.

Bertay, A. C., Demirgüç-Kunt, A. and Huizinga, H. (2013) 'Do we need big banks? Evidence on performance, strategy and market discipline', Journal of Financial Intermediation, 22(4), pp. 532–558. doi: 10.1016/j.jfi.2013.02.002.

Bessler, W. and Kurmann, P. (2014) 'Bank risk factors and changing risk exposures: Capital market evidence before and during the financial crisis', Journal of Financial Stability, 13, pp. 151–166. doi: 10.1016/j.jfs.2014.06.003.

Bessler, W., Kurmann, P. and Nohel, T. (2015) 'Time-varying systematic and idiosyncratic risk exposures of US bank holding companies', Journal of International Financial Markets, Institutions and Money, 35, pp. 45–68. doi: 10.1016/j.intfin.2014.11.009.

BIS (2011) 'The impact of sovereign credit risk on bank funding conditions', CGFS Papers, 43. Available at: https://www.bis.org/publ/cgfs43.htm.

BIS (2013) 'International banking and financial market developments', BIS Quarterly Review, December. Available at: https://www.bis.org/publ/qtrpdf/r_qt1312.pdf.

Bissoondoyal-Bheenick, E. and Treepongkaruna, S. (2011) 'An analysis of the determinants of bank ratings: comparison across ratings agencies', Australian Journal of Management, 36(3), pp. 405–424. doi: 10.1177/0312896211426676.

Blau, B. M., Brough, T. J. and Griffith, T. G. (2017) 'Bank opacity and the efficiency of stock prices', Journal of Banking and Finance, 76, pp. 32–47. doi: 10.1016/j.jbankfin.2016.11.026.

Bolton, P., Freixas, X. and Shapiro, J. (2012) 'The credit ratings game', Journal of Finance, 67(1), pp. 85–111. doi: 10.1111/j.1540-6261.2011.01708.x.

Bone, R. B. and Ribeiro, E. P. (2009) 'Conteúdo informacional dos ratings corporativos de empresas brasileiras, 1995-2007', in Anais do XXXVII Encontro Nacional de Economia [Proceedings of the 37th Brazilian Economics Meeting]. Foz do Iguaçu, Paraná: 8-11 December.

Bongaerts, D., Cremers, K. J. M. and Goetzmann, W. N. (2012) 'Tiebreaker : Certification and multiple credit ratings', Journal of Finance, 67(1), pp. 113–152. doi: 10.1111/j.1540-6261.2011.01709.x.

Böninghausen, B. and Zabel, M. (2015) 'Credit ratings and cross-border bond market spillovers', Journal of International Money and Finance, 53, pp. 115–136. doi: 10.1016/j.jimonfin.2014.12.007.

Boot, A. W., Milbourn, T. T. and Schmeits, A. (2006) 'Credit ratings as coordination mechanisms', Review of Financial Studies, 19(1), pp. 81–118. doi: 10.1093/rfs/hhj009.

Borensztein, E., Cowan, K. and Valenzuela, P. (2013) 'Sovereign ceilings "lite"? The impact of sovereign ratings on corporate ratings', Journal of Banking & Finance, 37(11), pp. 4014–4024. doi: 10.1016/j.jbankfin.2013.07.006.

Borraz, F., Fried, A. and Gianelli, D. (2011) 'Análisis de las calificaciones de riesgo soberano: el caso uruguayo', Documento de trabajo (Working paper) Banco Central del Uruguay. Banco Central del Uruguay, 003, pp. 71–99. Available at: https://www.bcu.gub.uy/Estadisticas-e-Indicadores/Documentos de Trabajo/3.2011.pdf.

Bowe, M. and Larik, W. (2014) 'Split ratings and differences in corporate credit rating policy between Moody's and Standard & Poor's', Financial Review, 49(4), pp. 713–734. doi: 10.1111/fire.12054.

Bruno, V., Cornaggia, J. and Cornaggia, K. J. (2016) 'Does regulatory certification affect the information content of credit ratings?', Management Science, 62(6), pp. 1578–1597. doi: 10.1287/mnsc.2015.2188.

Byoun, S., Fulkerson, J. A., Han, S. H. and Shin, Y. S. (2014) 'Are unsolicited ratings biased? Evidence from long-run stock performance', Journal of Banking & Finance, 42, pp. 326–338. doi: 10.1016/j.jbankfin.2014.02.005.

Byoun, S. (2014) 'Information content of unsolicited credit ratings and incentives of rating agencies: A theory', International Review of Economics & Finance, 33, pp. 338–349. doi: 10.1016/j.iref.2014.02.011.

Byrne, J. P. and Fiess, N. (2016) 'International capital flows to emerging markets: National and global determinants', Journal of International Money and Finance, 61, pp. 82–100. doi: 10.1016/j.jimonfin.2015.11.005.

Camanho, N., Deb, P. and Liu, Z. (2012) 'Credit rating and competition', 22nd Australasian Finance and Banking Conference 2009. (AFA 2011 Denver Meetings Paper), July. Available at: http://dx.doi.org/10.2139/ssrn.1573035.

Camara de Comercio de Bogota (2012) 'Laudo arbitral Banco Colpatria Multibanca Colpatria S.A. vs. Fitch Ratings Colombia S.A. SCV Abril 20 de 2012. [Arbitration Banco Colpatria Multibanca Colpatria S.A. vs. Fitch Ratings Colombia S.A. SCV April 20th 2012]'. Bogota. Available at: http://legal.legis.com.co/document?obra=laudosccb&document=laudosccb_d5b56e28d1f4011ae0430a010151011a.

Cameron, A. and Miller, D. L. (2015) 'A Practitioner's Guide to Cluster-Robust Inference', Journal of Human Resources, 50(2), pp. 317–372. doi: 10.3368/jhr.50.2.317.

Cameron, A. and Trivedi, P. (2010) Microeconometrics using Stata, revised edition. Rev. ed. 2. College Station, Texas: Stata Press.

Cantor, R. and Packer, F. (1997) 'Differences of opinion and selection bias in the credit rating industry', Journal of Banking & Finance, 21(10), pp. 1395–1417. doi: 10.1016/S0378-4266(97)00024-1.

Capital Intelligence (2019) Foreign currency and local currency ratings. Available at: http://www.ciratings.com/page/rating-definitions/foreign-local-currency-ratings (Accessed: 6 March 2019).

Caporale, G. M., Matousek, R. and Stewart, C. (2012) 'Ratings assignments: Lessons from international banks', Journal of International Money and Finance, 31(6), pp. 1593–1606. doi: 10.1016/j.jimonfin.2012.02.018.

Carvalho, P. V., Laux, P. A. and Pereira, J. P. (2014) 'The stability and accuracy of credit ratings', SSRN Electronic Journal. doi: 10.2139/ssrn.2504972.

Cavallo, E., Powell, A. and Rigobon, R. (2013) 'Do credit rating agencies add value? Evidence from the sovereign rating business', International Journal of Finance and Economics, 18(3), pp. 240–265. doi: 10.1002/ijfe.1461.

Chan, P. T., Edwards, V. and Walter, T. (2009) 'The information content of Australian credit ratings: A comparison between subscription and non-subscription-based credit rating agencies', Economic Systems, 33(1), pp. 22–44. doi: 10.1016/j.ecosys.2008.09.002.

Chen, M., Jeon, B. N., Wang, R. and Wu, J. (2015) 'Corruption and bank risk-taking: Evidence from emerging economies', Emerging Markets Review, 24, pp. 122–148. doi: 10.1016/j.ememar.2015.05.009.

Cinquegrana, P. (2009) 'The reform of the credit rating agencies: A comparative perspective', ECMI Policy Brief, 12, pp. 1–12. Available at: http://ssrn.com/abstract=1489743.

Cisneros, D., Lizarzaburu, E. R. and Salguero, J. Q. (2012) 'Credit Information in Emerging Markets: The Rating Agencies and Credit Risk Reports, Peruvian Experience', International Journal of Business and Management, 7(24), pp. 35–43. doi: 10.5539/ijbm.v7n24p35.

Correa, R. and Sapriza, H. (2014) 'Sovereign Debt Crises', in Berger, A. N., Molyneux, P., and Wilson, J. O. S. (eds) Oxford Handbook of Banking, Second edition. Oxford University Press. doi: 10.1093/oxfordhb/9780199688500.013.0030.

CSA (2012) Canadian securities regulators adopt regulatory regime for credit rating organisations, Canadian Securities Administrators. Available at: https://www.osc.gov.on.ca/en/NewsEvents_nr_20120127_csa-credit-rating.htm (Accessed: 28 May 2019).

CSRC (2007) [Order No. 50] Interim measures for the administration of credit rating business in the securities market, China Securities Regulatory Commission. Available at: http://www.csrc.gov.cn/pub/zjhpublic/zjh/200804/t20080418_14513.htm (Accessed: 28 May 2019).

Dahiya, S., Iannotta, G. and Navone, M. (2017) 'Firm opacity lies in the eye of the beholder', Financial Management, 46(3), pp. 553–592. doi: 10.1111/fima.12168.

De Jong, G. and van Houten, J. (2014) 'The impact of MNE cultural diversity on the internationalization-performance relationship', International Business Review, 23(1), pp. 313–326. doi: 10.1016/j.ibusrev.2013.05.005.

De Jonghe, O., Diepstraten, M. and Schepens, G. (2015) 'Banks' size, scope and systemic risk: What role for conflicts of interest?', Journal of Banking & Finance, 61, pp. S3–S13. doi: 10.1016/j.jbankfin.2014.12.024.

De Moor, L., Luitel, P., Sercu, P. and Vanpée, R. (2018) 'Subjectivity in sovereign credit ratings', Journal of Banking and Finance, 88, pp. 366–392. doi: 10.1016/j.jbankfin.2017.12.014.

Deb, P., Manning, M., Murphy, G., Penalver, A. and Toth, A. (2011) Whither the credit ratings industry?, Financial Stability Paper, Bank of England. 9. Available at: https://www.bankofengland.co.uk/financial-stability-paper/2011/whither-the-credit-ratings-industry.

Demirbag, M., Tatoglu, E. and Glaister, K. W. (2010) 'Institutional and transaction cost influences on partnership structure of foreign affiliates', MIR: Management International Review, 50(6), pp. 709–745. Available at: http://www.jstor.org/stable/41426821.

Devenow, A. and Welch, I. (1996) 'Rational herding in financial economics', European Economic Review, 40(3–5), pp. 603–615. doi: 10.1016/0014-2921(95)00073-9.

DFA (2010) Dodd-Frank Wall Street Reform and consumer protection act. United States Federal Reserve. Available at: https://fraser.stlouisfed.org/title/1031 (Accessed: 28 May 2019).

Di Pietra, R., McLeay, S. and Ronen, J. (2014) Accounting and regulation : New insights on governance, markets and institutions. New York, NY: Springer.

Dietrich, A. and Wanzenried, G. (2014) 'The determinants of commercial banking profitability in low-, middle-, and high-income countries', The Quarterly Review of Economics and Finance, 54(3), pp. 337–354. doi: 10.1016/j.qref.2014.03.001.

Drago, D. and Gallo, R. (2017) 'The impact of sovereign rating changes on the activity of European banks', Journal of Banking and Finance, 85, pp. 99–112. doi: 10.1016/j.jbankfin.2017.08.018.

Drehmann, M. and Tarashev, N. (2011) 'Systemic importance: some simple indicators', BIS Quarterly Review, (March), pp. 25–37. Available at: http://www.bis.org/publ/qtrpdf/r_qt1103e.pdf.

Duff, A. and Einig, S. (2009) 'Understanding credit ratings quality: Evidence from UK debt market participants', The British Accounting Review, 41(2), pp. 107–119. doi: 10.1016/j.bar.2009.02.001.

EBA (2015) ‘Risk Dashboard. Data as of Q4 2015’, European Banking Authority Risk Dashboard. Available at: https://publications.europa.eu/en/publication-detail/-/publication/250a4274-0205-11e6-b713-01aa75ed71a1/language-en.

Ebeke, C. and Lu, Y. (2015) ‘Emerging market local currency bond yields and foreign holdings – A fortune or misfortune?’, Journal of International Money and Finance, 59, pp. 203–219. doi: 10.1016/j.jimonfin.2015.07.006.

Ederington, L. H. (1986) ‘Why Split Ratings Occur’, Financial Management. l, 15(1), p. 37. doi: 10.2307/3665276.

Efing, M. and Hau, H. (2015) ‘Structured debt ratings: Evidence on conflicts of interest’, Journal of Financial Economics, 116(1), pp. 46–60. doi: 10.1016/j.jfineco.2014.11.009.

ESMA (2018) ‘Report on CRA market share calculation’, European Securities and Markets Authority. Paris, France, November(ESMA33-9–281). Available at: https://www.esma.europa.eu/sites/default/files/library/cra_market_share_calculation_2018.pdf.

European Commission (2015) ‘Study on the feasibility of alternatives to credit ratings’, European Commission Directorate-General for Financial Stability, Financial Services and Capital Markets Union, (December). doi: 10.2874/888173.

Federal Financial Institutions Examination Council (2016) Return on average assets for all U.S. Banks [USROA], Retrieved from FRED, Federal Reserve Bank of St. Louis. Available at: https://fred.stlouisfed.org/series/USROA (Accessed: 17 April 2017).

Ferreira, M. A. and Gama, P. M. (2007) ‘Does sovereign debt ratings news spill over to international stock markets?’, Journal of Banking & Finance, 31(10), pp. 3162–3182. doi: 10.1016/j.jbankfin.2006.12.006.

Ferri, G. (2004) ‘More analysts, better ratings: Do rating agencies invest enough in less developed countries?’, Journal of Applied Economics, 7(1), pp. 77–98. doi: 10.1080/15140326.2004.12040604.

Ferri, G. and Lacitignola, P. (2010) Does Europe need its own rating agencies? Dipartimento di Scienze economiche e metodi matematici - Universita di Bari. Available at: http://econpapers.repec.org/RePEc:bai:series:economia-series33.

Ferri, G., Lacitignola, P. and Lee, J. Y. (2013) ‘Foreign ownership and the credibility of national rating agencies: Evidence from Korea’, Journal of Comparative Economics, 41(3), pp. 762–776. doi: 10.1016/j.jce.2013.03.014.

Ferri, G. and Liu, L.-G. (2003) ‘How do global credit rating agencies rate firms from developing countries?’, Asian Economic Papers, 2(3), pp. 30–56. doi: 10.1162/asep.2003.2.3.30.

Ferri, G. and Liu, L. (2005) ‘Assessing the effort of rating agencies in emerging economies: Some empirical evidence’, European Journal of Finance, 11(3), pp. 283–295. doi: 10.1080/13518470500039246.

FINMA (2012) ‘Circular 2012 / 1 Credit rating agencies - Recognition of external credit assessment institutions (credit rating agencies)’, Swiss Financial Market Supervisory Authority, (Circ. 2012/1). Available at: https://www.finma.ch/en/documentation/circulars/.

FINMA (2018) Recognised credit rating agencies, Swiss Financial Market Supervisory Authority. Bern, Switzerland. Available at: www.finma.ch.

Fiordelisi, F. and Marqués-Ibañez, D. (2013) ‘Is bank default risk systematic?’, Journal of Banking and Finance, 37(6), pp. 2000–2010. doi: 10.1016/j.jbankfin.2013.01.004.

Fitch Ratings (2018a) ‘Bank Rating Criteria’, Master Criteria, (12 October 2018).

Fitch Ratings (2018b) ‘Rating Definitions’.

Fitch Ratings (2019) Form NRSRO Exhibit 4. Available at: https://www.fitchratings.com/site/regulatory.

Fitch Ratings Colombia S.A. (2009) ‘Fitch Ratings Colombia S.A. SCV reviso extraordinariamente las calificaciones homologadas de todos los establecimientos de credito y tambien aquellas calificaciones homologadas de emisiones que pudieran guardar una relacion con una calificacion de emisor’, Superintendencia Financiera de Colombia. Bogota, Colombia. Available at: https://www.superfinanciera.gov.co/inicio/informacion-relevante-61446.

Flannery, M. J., Kwan, S. H. and Nimalendran, M. (2004) ‘Market evidence on the opaqueness of banking firms’ assets’, Journal of Financial Economics, 71, pp. 419–460. doi: 10.1016/S0304-405X(03)00185-5.

Flannery, M. J., Kwan, S. H. and Nimalendran, M. (2013) ‘The 2007-2009 financial crisis and bank opaqueness’, Journal of Financial Intermediation, 22, pp. 55–84. doi: 10.1016/j.jfi.2012.08.001.

Fosu, S., Ntim, C. G., Coffie, W. and Murinde, V. (2017) ‘Bank opacity and risk-taking: Evidence from analysts’ forecasts’, Journal of Financial Stability, 33, pp. 81–95. doi: 10.1016/j.jfs.2017.10.009.

Fosu, S., Danso, A., Agyei-Boapeah, H., Ntim, C. G. and Murinde, V. (2018) ‘How does banking market power affect bank opacity? Evidence from analysts’ forecasts’, International Review of Financial Analysis, 60, pp. 38–52. doi: 10.1016/j.irfa.2018.08.015.

FPRI (2013) ‘The international discussions on the credit rating agencies and enhancing infraestructure to strengthen the regional credit rating capacity in the ASEAN+3 region’, Fiscal Policy Research Institute (FPRI), Thailand. Available at: http://www.asean.org/storage/images/2013/economic/fiscal policy research institute fpri.pdf.

FSA (2014) ‘Annual Report 2014’, Financial Services Agency Government of Japan. Available at: https://www.fsa.go.jp/en/about/Annual_Reports/2014.pdf.

Fulghieri, P., Strobl, G. and Xia, H. (2014) ‘The economics of solicited and unsolicited credit ratings’, Review of Financial Studies, 27(2), pp. 484–518. doi: 10.1093/rfs/hht072.

Gande, A. and Parsley, D. C. (2005) ‘News spillovers in the sovereign debt market’, Journal of Financial Economics, 75(3), pp. 691–734. doi: 10.1016/j.jfineco.2003.11.003.

Gonis, E., Paul, S. and Tucker, J. (2012) ‘Rating or no rating? That is the question: an empirical examination of UK companies’, European Journal of Finance, 18(8), pp. 709–735. doi: 10.1080/1351847X.2011.649215.

Goodell, J. W. and Goyal, A. (2018) 'What determines debt structure in emerging markets: Transaction costs or public monitoring?', International Review of Financial Analysis, 55, pp. 184–195. doi: 10.1016/j.irfa.2017.07.004.

Greene, W. W. H. . (2012) Econometric analysis. 7th ed., I, Prentice Hall. 7th ed., I. Edited by Pearson. Boston.

Griffin, J. M., Nickerson, J. and Tang, D. Y. (2013) 'Rating shopping or catering?An examination of the response to competitive pressure for CDO credit ratings', Review of Financial Studies, 26(9), pp. 2270–2310. doi: 10.1093/rfs/hht036.

Gropp, R. and Heider, F. (2010) 'The determinants of bank capital structure', Review of Finance, 14(4), pp. 587–622. doi: 10.1093/rof/rfp030.

Güttler, A. (2011) 'Lead-lag relationships and rating convergence among credit rating agencies', *Journal of Credit Risk*, 7(1). doi: 10.2139/ssrn.1488164.

Han, S. H., Shin, Y. S., Reinhart, W. and Moore, W. T. (2009) 'Market segmentation effects in corporate credit rating changes: The case of emerging markets', Journal of Financial Services Research, 35(2), pp. 141–166. doi: http://dx.doi.org/10.1007/s10693-008-0049-0.

Han, S. H., Moore, W. T., Shin, Y. S. and Yi, S. (2013) 'Unsolicited versus solicited: Credit ratings and bond yields', Journal of Financial Services Research, 43(3), pp. 293–319. doi: 10.1007/s10693-012-0137-z.

Han, S. H., Pagano, M. S. and Shin, Y. S. (2012) 'Rating agency reputation, the global financial crisis, and the cost of debt', Financial Management, 41(4), pp. 849–884. doi: 10.1111/j.1755-053X.2012.01204.x.

Hartelius, K., Kashiwase, K. and Kodres, L. (2008) 'Emerging market spread compression: is it real or is it liquidity', International Monetary Fund Working Paper. (WP/08/10). Available at: https://www.imf.org/external/pubs/cat/longres.aspx?sk=21546.0.

Haselmann, R. and Wachtel, P. (2011) 'Foreign banks in syndicated loan markets', Journal of Banking & Finance, 35(10), pp. 2679–2689. doi: 10.1016/j.jbankfin.2011.02.023.

Hau, H., Langfield, S. and Marques-Ibanez, D. (2013) 'Bank ratings: what determines their quality?', Economic Policy, 28(74), pp. 289–333. doi: 10.1111/1468-0327.12009.

HR Ratings (2019) HR Rating scales, HR Ratings. Available at: https://www.hrratings.com/methodology/rating_scales.xhtml (Accessed: 29 May 2019).

Hu, X., Huang, H., Pan, Z. and Shi, J. (2019) 'Information asymmetry and credit rating: A quasi-natural experiment from China', Journal of Banking and Finance, 106, pp. 132–152. doi: 10.1016/j.jbankfin.2019.06.003.

Huang, Y. L. and Shen, C. H. (2015) 'The sovereign effect on bank credit ratings', Journal of Financial Services Research, 47, pp. 341–379. doi: 10.1007/s10693-014-0193-7.

Huber, P. J. (1967) 'The behavior of maximum likelihood estimates under nonstandard conditions', in Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, Volume 1: Statistics. Berkeley, California, pp. 221–233. Available at: http://projecteuclid.org/euclid.bsmsp/1200512988.

Hyytinen, A. and Pajarinen, M. (2008) 'Opacity of young businesses: Evidence from rating disagreements', Journal of Banking and Finance, 32(7), pp. 1234–1241. doi: 10.1016/j.jbankfin.2007.10.006.

Iannotta, G. (2006) 'Testing for opaqueness in the European banking industry: Evidence from bond credit ratings', Journal of Financial Services Research, 30(3), pp. 287–309. doi: 10.1007/s10693-006-0420-y.

IBAN (2019) Country codes Alpha-2 & Alpha-3, IBAN. Available at: https://www.iban.com/country-codes (Accessed: 25 September 2019).

IMF (2010) 'Chapter 3. The uses and abuses of sovereign credit ratings', Global Financial Stability Report, (October). Global Financial Stability Report, October 2010: Sovereigns, Funding, and Systemic Liquidity. USA: International Monetary Fund. doi: 10.5089/9781589069480.082

IMF (2018) World Economic Outlook, October 2018: Challenges to Steady Growth, World Economic Outlook. Washington, D.C.: International Monetary Fund (World Economic Outlook). doi: 10.5089/9781484376799.081.

IOSCO (2013) 'Supervisory Colleges for Credit Rating Agencies Final Report', The board of the International Organization of Securities Commissions, (FR08/13). Available at: https://www.iosco.org/publications/.

Ismail, A., Oh, S. and Arsyad, N. (2015) 'Split ratings and debt-signaling in bond markets: A note', Review of Financial Economics, 24(1), pp. 36–41. doi: 10.1016/j.rfe.2014.12.003.

Jewell, J. and Livingston, M. (1998) 'Split ratings, bond yields, and underwriter spreads', Journal of Financial Research, 21(2), pp. 185–204. doi: 10.1111/j.1475-6803.1998.tb00679.x.

Jiang, J. (Xuefeng), Harris Stanford, M. and Xie, Y. (2012) 'Does it matter who pays for bond ratings? Historical evidence', Journal of Financial Economics, 105(3), pp. 607–621. doi: 10.1016/j.jfineco.2012.04.001.

Jiang, X. and Packer, F. (2017) 'Credit ratings of domestic and global agencies : What drives the differences in China and how are they priced?', BIS Working Papers No. 648. Available at: https://www.bis.org/publ/work648.htm.

Jiang, X. and Packer, F. (2019) 'Credit ratings of Chinese firms by domestic and global agencies: Assessing the determinants and impact', Journal of Banking and Finance Finance, 105, pp. 178–193. doi: 10.1016/j.jbankfin.2019.05.011.

Jiménez, G., Ongena, S., Peydró, J. and Saurina, J. (2010) 'Credit supply identifying channels with loan applications and granted loans', European Central Bank Working Paper Series No. 1179. Available at: https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1179.pdf?07d2752af37dc4e06444fb89e38ea4b2.

Jiménez, G., Ongena, S., Peydró, J. and Saurina, J. (2012) 'Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications', American Economic Review, 102(5), pp. 2301–2326.

Joe, D. Y. and Oh, F. D. (2017) 'Did foreign ownership of Korean credit rating agencies improve their ratings?', Contemporary Economic Policy, 35(1), pp. 193–200. doi: 10.1111/coep.12176.

Jones, J. S., Lee, W. Y. and Yeager, T. J. (2013) 'Valuation and systemic risk consequences of bank opacity', Journal of Banking and Finance, 37(3), pp. 693–706. doi: 10.1016/j.jbankfin.2012.10.028.

Juambeltz, A. (2014) 'Las calificadoras de riesgo, su rol en los mercados financieros y el caso Uruguayo', Revista Iberoamericana de Ciencias Empresariales y Economía, 4(4). Available at: http://200.58.147.92/revistas/ricee/index.php/ricee/article/view/32.

Karminsky, A. M. and Khromova, E. (2016) 'Extended Modeling of Banks' Credit Ratings', Procedia Computer Science, 91, pp. 201–210. doi: 10.1016/j.procs.2016.07.058.

Kaufmann, D., Kraay, A. and Mastruzzi, M. (2010) 'The Worldwide Governance Indicators: Methodology and Analytical Issues', Policy Research Working Paper No. 5430. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1682130.

Kim, S.-J. and Wu, E. (2008) 'Sovereign credit ratings, capital flows and financial sector development in emerging markets', Emerging Markets Review, 9(1), pp. 17–39. doi: 10.1016/j.ememar.2007.06.001.

Kisgen, D. J. and Strahan, P. E. (2010) 'Do regulations based on credit ratings affect a firm's cost of capital?', Review of Financial Studies, 23(12), pp. 4324–4347. doi: 10.1093/rfs/hhq077.

Klusak, P., Alsakka, R. and ap Gwilym, O. (2017) 'Does the disclosure of unsolicited sovereign rating status affect bank ratings?', British Accounting Review, 49(2), pp. 194–210. doi: 10.1016/j.bar.2016.08.004.

Laeven, L., Ratnovski, L. and Tong, H. (2016) 'Bank size, capital, and systemic risk: Some international evidence', Journal of Banking and Finance, 69, pp. S25–S34. doi: 10.1016/j.jbankfin.2015.06.022.

Langohr, H. and Langohr, P. (2010) Preview of the rating agencies and their credit ratings what they are, how they work, and why they are relevant. Edited by John Wiley & Sons Ltd. New York, NY. doi: 10.1002/9781119208785.

Lemmon, M. L., Roberts, M. R. and Zender, J. F. (2008) 'Back to the beginning: persistence and the cross-section of corporate capital structure', The Journal of Finance, 63(4), pp. 1575–1608. Available at: http://www.jstor.org/stable/25094484.

Lemmon, M. and Roberts, M. R. (2010) 'The response of corporate financing and investment to changes in the supply of credit', Journal of Financial and Quantitative Analysis, 45(03), pp. 555–587.

Leung, W. S., Taylor, N. and Evans, K. P. (2015) 'The determinants of bank risks: Evidence from the recent financial crisis', Journal of International Financial Markets, Institutions and Money, 34, pp. 277–293. doi: 10.1016/j.intfin.2014.11.012.

Li, J., Shin, Y. S. and Moore, W. (2006) 'Reactions of Japanese markets to changes in credit ratings by global and local agencies', Journal of Banking & Finance, 30(3), pp. 1007–1021. doi: 10.1016/j.jbankfin.2005.05.026.

Livingston, M., Naranjo, A. and Zhou, L. (2007) 'Asset opaqueness and split bond ratings', Financial Management, 36(3), pp. 49–62. doi: 10.1111/j.1755-053X.2007.tb00080.x.

Livingston, M., Naranjo, A. and Zhou, L. (2008) ‘Split bond ratings and rating migration’, Journal of Banking and Finance, 32(8), pp. 1613–1624. doi: 10.1016/j.jbankfin.2007.11.019.

Livingston, M., Poon, W. P. H. and Zhou, L. (2018) ‘Are Chinese credit ratings relevant? A study of the Chinese bond market and credit rating industry’, Journal of Banking & Finance, 87, pp. 216–232. doi: 10.1016/j.jbankfin.2017.09.020.

Livingston, M., Wei, J. D. and Zhou, L. (2010) ‘Moody’s and S&P ratings: Are they equivalent? Conservative ratings and split rated bond yields’, Journal of Money, Credit and Banking, 42(7), pp. 1267–1293. doi: 10.1111/j.1538-4616.2010.00341.x.

Livingston, M. and Zhou, L. (2010) ‘Split bond ratings and information opacity premiums’, Financial Management, 39(2), pp. 515–532. doi: 10.1111/j.1755-053X.2010.01082.x.

Livingston, M. and Zhou, L. (2016) ‘Information opacity and Fitch bond ratings’, Journal of Financial Research, 39(4), pp. 329–357. doi: 10.1111/jfir.12110.

Lugo, S., Croce, A. and Faff, R. (2015) ‘Herding behavior and rating convergence among credit rating agencies: evidence from the subprime crisis’, Review of Finance, 19(4), pp. 1703–1731. doi: 10.1093/rof/rfu028.

Luitel, P., Vanpée, R. and De Moor, L. (2016) ‘Pernicious effects: How the credit rating agencies disadvantage emerging markets’, Research in International Business and Finance, 38, pp. 286–298. doi: 10.1016/j.ribaf.2016.04.009.

Mählmann, T. (2009) ‘Multiple credit ratings, cost of debt and self-selection’, Journal of Business Finance and Accounting, 36(9–10), pp. 1228–1251. doi: 10.1111/j.1468-5957.2009.02168.x.

Marandola, G. (2015) ‘Local credit rating agencies: Is their economic role underrated?’, SSRN Electronic Journal. doi: 10.2139/ssrn.2548464.

Marandola, G. (2016) ‘Local credit rating agencies: a new dataset’, Research in International Business and Finance, 38, pp. 83–103. doi: 10.1016/j.ribaf.2016.03.006.

Massa, M. and Žaldokas, A. (2014) ‘Investor base and corporate borrowing: Evidence from international bonds’, Journal of International Economics, 92(1), pp. 95–110. doi: 10.1016/j.jinteco.2013.11.002.

Mathis, J., McAndrews, J. and Rochet, J.-C. (2009) ‘Rating the raters: Are reputation concerns powerful enough to discipline rating agencies?’, Journal of Monetary Economics, 56(5), pp. 657–674. doi: 10.1016/j.jmoneco.2009.04.004.

Milidonis, A. (2013) ‘Compensation incentives of credit rating agencies and predictability of changes in bond ratings and financial strength ratings’, Journal of Banking & Finance, 37(9), pp. 3716–3732. doi: 10.1016/j.jbankfin.2013.04.032.

Moody’s (2015a) ‘Emerging Markets Sovereign Default Measures Diverge’, Sovereign Risk Report, (November).

Moody’s (2015b) ‘Rating Action: Moody’s downgrades Russia’s sovereign rating to Ba1 from Baa3; outlook negative’, Moody’s Investor Service, (20 Feb 2015).

Moody’s (2017) ‘Rating Action : Moody’s affirms SME Development Bank of Thailand’s Baa2 deposit rating ; upgrades BCA to b3 from caa1’, Global Credit Research, (12 Jan 2017).

Moody's (2018a) Annual Report 2018. doi: 10.3934/Math.2019.1.166.

Moody's (2018b) 'Form 10-K United States Securities and Exchange Commission'. Available at: https://ir.moodys.com/news-and-financials/sec-filings/default.aspx.

Moody's (2018c) Rating Methodology: Banks, August 2018. Available at: https://www.moodys.com/researchdocumentcontentpage.aspx?docid=PBC_1128883.

Moody's (2019a) Partnerships & Alliances. Available at: https://www.moodys.com/Pages/atc002001007.aspx (Accessed: 28 May 2019).

Moody's (2019b) 'Rating symbols and definitions', Moody's Investor Service, (February).

Morgan, D. P. (2002) 'Rating banks: Risk and uncertainty in an opaque industry', American Economic Review, 92(4), pp. 874–888. doi: 10.1257/00028280260344506.

Morkoetter, S., Stebler, R. and Westerfeld, S. (2017) 'Competition in the credit rating industry: Benefits for investors and issuers', Journal of Banking & Finance, 75, pp. 235–257. doi: 10.1016/j.jbankfin.2016.09.001.

Nagano, M. (2018) 'What promotes/prevents firm bond issuance in emerging economies: Bank–firm relationship or information asymmetry?', International Review of Economics & Finance, 56, pp. 161–177. doi: 10.1016/j.iref.2017.10.022.

Nogueira, A. and Fonseca, A. M. A. (2013) 'The impact of credit rating changes in Latin American stock markets', BAR-Brazilian Administration Review. SciELO Brasil, 10(4), pp. 439–461. doi: 10.1590/S1807-76922013000400005.

Oh, K. W. and Kim, H. A. (2019) 'Are inflated domestic credit ratings relative to global ratings associated with peer firms' investment decisions? Evidence from Korea', Japan and the World Economy, 51, p. 100956. doi: 10.1016/j.japwor.2019.04.001.

Opp, C. C., Opp, M. M. and Harris, M. (2013) 'Rating agencies in the face of regulation', Journal of Financial Economics, 108(1), pp. 46–61. doi: 10.1016/j.jfineco.2012.10.011.

Packer, F. (2000) 'Credit ratings and the Japanese corporate bond market', Institute for Monetary and Economic Studies (IMES) Discussion Paper No. 2000-E-9. Available at: http://www.imes.boj.or.jp/research/papers/english/00-E-09.pdf.

Pan, Y. (1996) 'Influences on foreign equity ownership level in joint ventures in China', Journal of International Business Studies, 27(1), pp. 1–26. Available at: http://www.jstor.org/stable/155369.

Park, D., Taniguchi, K. and Tian, S. (2019) 'Determinants of foreign and domestic investment bias in global bond markets: Some empirical evidence', North American Journal of Economics and Finance, 49, pp. 287–303. doi: 10.1016/j.najef.2019.04.012.

Park, G. and Lee, H.-Y. (2018) 'Opportunistic behaviors of credit rating agencies and bond issuers', Pacific-Basin Finance Journal, 47, pp. 39–59. doi: 10.1016/j.pacfin.2017.11.003.

Park, J. (2012) 'Corruption, soundness of the banking sector, and economic growth: A cross-country study', Journal of International Money and Finance, 31(5), pp. 907–929. doi: 10.1016/j.jimonfin.2011.07.007.

PCR (2019) 'Rating regional PCR - Metodologias', Pacific Credit Rating. Available at: https://www.ratingspcr.com/application/files/8715/5361/9772/Rating_Regional_PCR.pdf.

Poon, W. P. H. and Chan, K. C. (2008) 'An empirical examination of the informational content of credit ratings in China', Journal of Business Research, 61(7), pp. 790–797. doi: 10.1016/j.jbusres.2007.08.001.

Poon, W. P. H., Lee, J. and Gup, B. E. (2009) 'Do solicitations matter in bank credit ratings? Results from a study of 72 countries', Journal of Money, Credit and Banking, 41(2–3), pp. 285–314. doi: 10.1111/j.1538-4616.2009.00206.x.

Purda, L. D. (2005) 'Mergers in the bond rating industry: does rating provider matter?', Journal of Multinational Financial Management, 15(2), pp. 155–169. doi: 10.1016/j.mulfin.2004.08.002.

Reeb, D. M., Mansi, S. A. and Allee, J. M. (2001) 'Firm internationalization and the cost of debt financing: Evidence from non-provisional publicly traded debt', Journal of Financial and Quantitative Analysis, 36(3), pp. 395–414. doi: 10.2307/2676289.

Rhoades, S. A. (1993) 'The Herfindahl-Hirschman Index', FRASER Federal Reserve Bank of St. Luis. Federal Reserve Bulletin : March 1993. Available at: http://fraser.stlouisfed.org/.

Rose, A. K. and Spiegel, M. M. (2009) 'International financial remoteness and macroeconomic volatility', Journal of Development Economics, 89(2), pp. 250–257. doi: 10.1016/j.jdeveco.2008.04.005.

S&P (2011a) 'Banking industry country risk assessment methodology and assumptions analytical contacts', S&P RatingsDirect - Criteria article, (November). Available at: https://www.maalot.co.il/Publications/MT20170717184534.pdf.

S&P (2011b) Banks: Rating methodology and assumptions, S&P Rating Criteria | Financial Institutions | Banks. Available at: https://www.standardandpoors.com/en_US/web/guest/article/-/view/sourceId/6921376 (Accessed: 26 April 2019).

S&P (2011c) 'Revised bank criteria applied to 18 Russian banks and core subsidiaries', Global Credit Portal - RatingsDirect, (December).

S&P (2011d) 'Standard & Poor ' s applies its revised bank criteria to 37 of the largest rated banks and certain subsidiaries', Global Credit Portal - RatingsDirect, (November).

S&P (2013) Country Risk Assessment Methodology And Assumptions. Available at: www.spglobal.com/ratingsdirect (Accessed: 23 January 2020).

S&P (2017) 'S&P Global Ratings confirma calificaciones de " mxAAA " y " mxA-1 + " de American Express Bank (México); la perspectiva se mantiene estable', Comunicado de Prensa - S&P Global Ratings, (November), pp. 1–6.

S&P (2018a) S&P Global Ratings Definitions, S&P Global. Available at: https://www.standardandpoors.com/en_US/web/guest/article/-/view/sourceId/504352 (Accessed: 28 May 2019).

S&P (2018b) 'Transparency report 2018', S&P Global Ratings Europe Limited, (December). Available at: https://www.standardandpoors.com/en_US/web/guest/regulatory/disclosures. (Accessed: 28 May 2019).

S&P Global (2019) 2019 Investor fact book. doi: 10.1300/j122v11n01_06.

S&P Global Ratings (2016) Why emerging market sovereign ratings are falling while portfolio inflows are rising. Available at: https://www.spratings.com/documents/20184/908545/SR_em,Article11116/7d104edc-b247-41e0-88cf-0790496e33f8 (Accessed: 8 August 2019).

S&P Global Ratings (2018) Form NRSRO Exibit 4. Available at: https://www.standardandpoors.com/en_US/web/guest/regulatory/form-nrsro.

Sahay, R., Arora, V., Arvanitis, T., Faruqee, H., N'Diaye, P. and Mancini-Griffoli, T. (2014) 'Emerging market volatility: lessons from the taper tantrum', IMF Staff Discussion Note, (SDN/14/09). Available at: https://www.imf.org/external/pubs/ft/sdn/2014/sdn1409.pdf.

Saka, H. (2018) 'Are sovereign ratings by CRAs consistent?', PANOECONOMICUS, 65(1), pp. 95–115. doi: 10.2298/PAN150311002S.

Salvador, C., Fernández de Guevara, J. and Pastor, J. M. (2018) 'The adjustment of bank ratings in the financial crisis: International evidence', North American Journal of Economics and Finance, 44, pp. 289–313. doi: 10.1016/j.najef.2018.01.001.

Salvador, C., Pastor, J. M. and Fernández de Guevara, J. (2014) 'Impact of the subprime crisis on bank ratings: The effect of the hardening of rating policies and worsening of solvency', Journal of Financial Stability, 11(1), pp. 13–31. doi: 10.1016/j.jfs.2013.10.005.

Schmukler, S. L. and Claessens, S. (2007) 'International financial integration through equity markets : which firms from which countries go global?', International Monetary Fund Working Paper No. 04/138. USA. doi: http://dx.doi.org/10.5089/9781451867022.001.

SEC (2018) Annual report on nationally recognized statistical rating organizations. Available at: https://www.sec.gov/ocr/reportspubs/annual-reports/2018-annual-report-on-nrsros.pdf.

Shen, C. H., Huang, Y. L. and Hasan, I. (2012) 'Asymmetric benchmarking in bank credit rating', Journal of International Financial Markets, Institutions and Money, 22(1), pp. 171–193. doi: 10.1016/j.intfin.2011.08.004.

Shin, Y. S. and Moore, W. (2003) 'Explaining credit rating differences between Japanese and U.S. agencies', Review of Financial Economics, 12(4), pp. 327–344. doi: 10.1016/j.rfe.2003.07.004.

Skreta, V. and Veldkamp, L. (2009) 'Ratings shopping and asset complexity: A theory of ratings inflation', Journal of Monetary Economics, 56(5), pp. 678–695. doi: 10.1016/j.jmoneco.2009.04.006.

Spatt, C. (2009) 'Discussion of "'Ratings shopping and asset complexity: A theory of ratings inflation'"', Journal of Monetary Economics, 56, pp. 696–699. doi: 10.1016/j.jmoneco.2009.05.001.

Tennant, D. F., Tracey, M. R. and King, D. W. (2018) 'Sovereign credit rating: Evidence of bias against poor countries', North American Journal of Economics and Finance. doi: 10.1016/j.najef.2018.11.006.

Tennant, D. and Sutherland, R. (2014) 'What types of banks profit most from fees charged? A cross-country examination of bank-specific and country-level determinants', Journal of Banking & Finance, 49, pp. 178–190. doi: 10.1016/j.jbankfin.2014.08.023.

Thakur, B. P. S. and Kannadhasan, M. (2019) ‘Corruption and cash holdings: Evidence from emerging market economies’, Emerging Markets Review, 38, pp. 1–17. doi: 10.1016/j.ememar.2018.11.008.

Thompson, S. B. (2011) ‘Simple formulas for standard errors that cluster by both firm and time’, Journal of Financial Economics, 99(1), pp. 1–10. doi: 10.1016/j.jfineco.2010.08.016.

Toader, T., Onofrei, M., Popescu, A.-I. and Andrieș, A. M. (2018) ‘Corruption and banking stability: Evidence from emerging economies’, Emerging Markets Finance and Trade, 54(3), pp. 591–617. doi: 10.1080/1540496X.2017.1411257.

Todhanakasem, W. (2001) ‘A domestic credit rating agency in an emerging asian country: the TRIS experience’, in Bond Market Development in Asia. OECD READ edition, pp. 341–346. doi: http://dx.doi.org/10.1787/9789264192225-en.

Transparency International (2016) Corruption Perceptions Index 2016 : Full Source Description. Available at: https://www.transparency.org/news/feature/corruption_perceptions_index_2016.

Tsunoda, J., Ahmed, M. and Islam, M. T. (2013) ‘Regulatory framework and role of domestic credit rating agencies in Bangladesh’, ADB South Asia Working Paper Series No. 21. Asian Development Bank. Available at: https://think-asia.org/handle/11540/2293.

Uhlenbruck, K. (2004) ‘Developing acquired foreign subsidiaries: the experience of MNEs in transition economies’, Journal of International Business Studies. Palgrave Macmillan Journals, 35(2), pp. 109–123. Available at: http://www.jstor.org/stable/3875246.

UNCTAD (2017) Trade and Development Report 2017 – Beyond Austerity: Towards A Global New Deal. Available at: https://unctad.org/en/PublicationsLibrary/tdr2017_en.pdf (Accessed: 29 July 2019).

Vazquez, F. and Federico, P. (2015) ‘Bank funding structures and risk: Evidence from the global financial crisis’, Journal of Banking & Finance, 61, pp. 1–14. doi: 10.1016/j.jbankfin.2015.08.023.

Vleugels, R. (2011) ‘Overview of all FOI laws’, Fringe Special, October.

Vo, X. V., Nguyen, D. P., Ho, V. T. and Nguyen, T. T. (2017) ‘Where do the advanced countries invest? An investigation of capital flows from advanced countries to emerging economies’, Journal of International Financial Markets, Institutions and Money, 51, pp. 142–154. doi: 10.1016/j.intfin.2017.09.004.

Vu, H., Alsakka, R. and ap Gwilym, O. (2015) ‘The credit signals that matter most for sovereign bond spreads with split rating’, Journal of International Money and Finance, 53, pp. 174–191. doi: 10.1016/j.jimonfin.2015.01.005.

Vu, H., Alsakka, R. and ap Gwilym, O. (2017) ‘What drives differences of opinion in sovereign ratings? The roles of information disclosure and political risk’, International Journal of Finance & Economics, 22(3), pp. 216–233. doi: 10.1002/ijfe.1579.

Weill, L. (2011a) ‘Does corruption hamper bank lending? Macro and micro evidence’, Empirical Economics, 41(1), pp. 25–42. doi: 10.1007/s00181-010-0393-4.

Weill, L. (2011b) ‘How corruption affects bank lending in Russia’, Economic Systems, 35(2), pp. 230–243. doi: 10.1016/j.ecosys.2010.05.005.

Weiß, G. N. F., Bostandzic, D. and Neumann, S. (2014) ‘What factors drive systemic risk during international financial crises?’, Journal of Banking and Finance, 41(1), pp. 78–96. doi: 10.1016/j.jbankfin.2014.01.001.

White, H. (1980) ‘A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity’, Econometrica, 48(4), pp. 817–838. doi: 10.2307/1912934.

White, L. J. (2010) ‘Markets: the credit rating agencies’, Journal of Economic Perspectives, 24(2), pp. 211–226. doi: 10.1257/jep.24.2.211.

Williams, G., Alsakka, R. and ap Gwilym, O. (2013) ‘The impact of sovereign rating actions on bank ratings in emerging markets’, Journal of Banking & Finance, 37(2), pp. 563–577. doi: 10.1016/j.jbankfin.2012.09.021.

Williams, G., Alsakka, R. and ap Gwilym, O. (2015) ‘Does sovereign creditworthiness affect bank valuations in emerging markets?’, Journal of International Financial Markets, Institutions and Money, 36, pp. 113–129. doi: 10.1016/j.intfin.2015.02.001.

Williams, R. (2012) ‘Using the margins command to estimate and interpret adjusted predictions and marginal effects’, The Stata Journal, 12(2), pp. 308–331. Available at: http://www.stata-journal.com.

Williams, R. (2015) ‘Interpreting interaction effects; Interaction effects and centering’, University of Notre Dame. Available at: http://www.nd.edu/~rwilliam/stats/StataHighlights.html (Accessed: 12 February 2020).

Xia, H. (2014) ‘Can investor-paid credit rating agencies improve the information quality of issuer-paid rating agencies?’, Journal of Financial Economics, 111(2), pp. 450–468. doi: 10.1016/j.jfineco.2013.10.015.

Yalta, A. T. and Yalta, A. Y. (2018) ‘Are credit rating agencies regionally biased?’, Economic Systems, 42(4), pp. 682–694. doi: 10.1016/j.ecosys.2018.08.001.

Yang, H., Ahn, H.-J., Kim, M. H. and Ryu, D. (2017) ‘Information asymmetry and investor trading behavior around bond rating change announcements’, Emerging Markets Review, 32, pp. 38–51. doi: 10.1016/j.ememar.2017.05.004.

Yiu, D. and Makino, S. (2002) ‘The choice between joint venture and wholly owned subsidiary: an institutional perspective’, Organization Science, 13(6), pp. 667–683. Available at: http://www.jstor.org/stable/3086087.